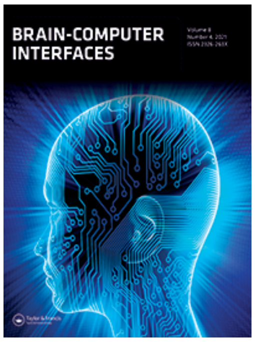

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SPECIAL ISSUE

A functional BCI model by the P2731 working group: control interface

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ABSTRACT
In order to facilitate communication and collaboration between researchers, Brain–computer interfaces (BCI) require a generally applicable functional model as well as a common vocabulary. The IEEE P2731 working group is in the process of developing such a functional model and a lexicon of BCI terminology. Such a functional model has multiple aspects including the control interface, physiology, transducers, etc. This current paper focuses on the control interface aspects of that model. Having a generally applicable control interface model will facilitate interdisciplinar y research and communication. The control interface is a critical part of the functional model and is described in this current paper. The control interface presented intentionally is intentionally kept general in order to be widely applicable. Some details are specific to a particular application and are thus left to those applications. It does contain the encoder (which also contains a decoder), with a feedback submodule.

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BCI; BCI control interface; BCI encoder

1. Introduction

Brain–computer interface (BCI) is not a new technology. Electroencephalograph (EEG) was first introduced in 1875. BCI has expanded to include Functional Magnetic Resonance Imaging (fMRI) [1], Functional near-infrared spectroscopy [2], Magnetoencephalography (MEG) [3], and many other techniques allow the recording of brain signals. Steady-state visually evoked potential (SSVEP) [4] provide signals that are responses to visual stimuli and can be measured by BCI. All of these various technologies are well described in current literature. However, despite over a century of research, there can be a lack of cohesion in terminology. The IEEE P2731 workgroup is working on a common terminology that could be widely used by a broad range of BCI researchers. The work of the IEEE P2731 working group is ongoing. This current paper is part of a special issue consisting of papers written by various subgroups of the P2731 working group, each describing a portion of the work being done. This is, by definition, incomplete work. One purpose of publishing work in progress is to give the wider BCI community an opportunity to provide input.

It should be noted that there are existing BCI glossary's [5,6], and those have been referenced in the work of the IEEE P2731 working group. The goal of the working group IEEE P2731 is not to supplant existing vocabularies, but to bring diverse vocabularies together into a coherent standard for BCI terminology. While there is extensive overlap in current vocabularies there are also areas of inconsistency. A standardized vocabulary addresses that issue. Integrating existing vocabularies, and filling any gaps therein is necessary to facilitate research communications. This working group's vocabulary will fulfill that goal and will be standardized by the IEEE.

The glossary is also being concurrently developed with a universal functional model for BCI. It should be apparent that with the diversity of BCI applications, a universal functional model will, by definition, need to be broad. The ability to be applicable to all areas of BCI research necessitates a certain lack of granularity in the functional model.

Applications for BCI are being continuously developed, and new applications are emerging frequently. The encoding required is often determined by the specific application, or a particular task that needs to be achieved. The

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control interface may therefore be defined by the characteristics of the control interface including operator state (active/passive), bit rate, error approximation, etc. In this paper, we review the various control interface's seen in literature, describe the control interface model proposed by the P2731 working group and discuss the application of the model to standardize and improve communication within the BCI community and beyond. This paper's organization is as follows: Section II presents the literature review concerning different control interface methodologies. Section III describes the proposed model of the P2731 working group. In Section IV, the authors show the application of the model. Finally, in Section V, conclusions of this work are provided

2. Review of literature

There currently exist frameworks for the design of BCI [7]. Such frameworks tend to be focused on specific BCI applications. This means that while such frameworks are quite effective, their efficacy may not be broadly applicable to the diverse areas of BCI research. The current study is focused specifically on the control interface. The term control interface was first applied to BCI in 2003 by Mason and Birch [7]. The Control Interface (CI) collects data extracted by the signal processing of the transducer in a BCI system. (Please see the paper on the transducer from IEEE P2731 workgroup also in this special issue.) And the control interface also sends data back to the transducer, usually in the form of feedback. Transducers tend to alternate between sending signals and receiving feedback [10]. There are existing standards that support transducer interfaces, including the IEEE P1451.5 Standard for a Smart Transducer Interface [11].

The control interface converts outputs from the transducer into commands applied to actuators and other systems in the BCI system. It also applies the relevant BCI paradigm (e.g. P300 wave) to drive feedback and generate the desired actions or stimuli if-and-when required. The P300 wave is only one example of a signal processed by a BCI. However, the P300 is illustrative of the type of signal that a BCI will process. The P300 wave is an event-related brain potential that refers to a spike in activity approximately 300 ms following presentation of the target stimulus [8]. Recent work has included using Augmented Reality in conjunction with P300 BCI [12]. This continued expansion of how to utilize signals presents yet more diversity in control interface design.

Ramadan and Vasilakos [13] described the importance of the control interface. Their study described the preprocessing, feature extraction, and signal classifications as precursors to control signals. While their study was broader than just control interface, the study demonstrated that the control interface is a critical element of BCI. This strongly indicates that a functional model, including a control interface is an important component to facilitate communication among researchers. There is some specificity of the control interface to particular applications. This may seem to be an impediment to generalizable control interface terminology and a universal control interface as an aspect of a functional model for BCI. However, that is not the case. It is common in systems engineering to defined broad functionality that is applicable to many different specific implementations [14]. This broadly applicable approach is the approach being used with the P2731 working group functional model. Figure 1 shows an overview of the control interface portion of the BCI functional model.

In the universal model of the control interface, the encoder maps sequences of logical symbols, such as cube rotation, flashing alphabets, etc., into semantic symbols, such as typing a character, driving a wheelchair, etc [9].

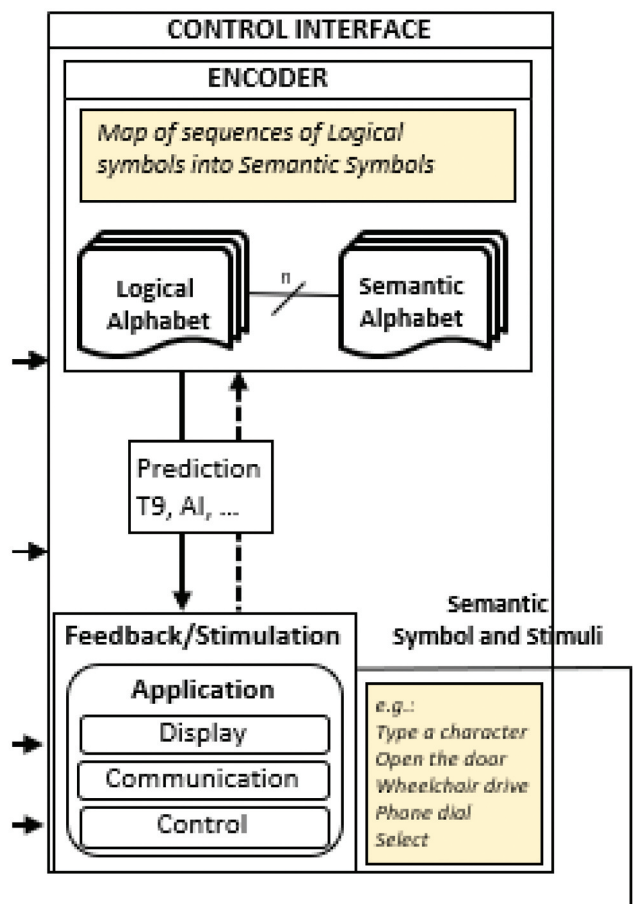

Figure 1. Block diagram of the control interface proposed by the P2731 working group showing the encoder and the feedback modules. Note there are inputs depicted in Figure 1. These will be related to other aspects of the functional model that are covered in other papers in this special issue. In order to see the entire functional model, refer to this special issues editorial.

Feedback functionality can be accomplished via control messages, display, and communication protocols. The form of feedback is often used to also describe the BCI application, and it is commonly used interchangeably to describe a particular system. However, they are functionally distinct.

Design for BCI has focused on a wide range of approaches. Much of the research regarding control interfaces for BCI have been for very specific purposes. Some studies have focused on specific attributes of the BCI interface such as types of electrodes used [15]. In recent years, wireless control interface modalities have been the focus of research [16]. Each control interface has its stipulated requirement of the logical to semantic symbol mapping and the feedback. Table 1 also provides the different types of control interfaces and the respective input and outputs to the control interface. Each type of control interface also has variations in complexity of control. BCI control interfaces may therefore be classified in different ways but the three most common classifications will be elaborated on here.

(1) Utility control interfaces may be classified as assistive or augmentative. Assistive BCIs are frequently designed from a utilitarian perspective [17]. Control of specific prosthetic and assistive devices has also been the focus of BCI interface studies [18]. One application is the control of robotic arm systems [19]. Robotic control has been further refined to implement utilization of EEG-Based control of assistive technologies for patients with lower limb dysfunction [20][21]. Spellers, for example, are also primarily assistive technology used in healthcare. Beyond health-care settings, there has even been research into areas, such as controlling unmanned aerial vehicles via BCI interfaces [22], games, applications in robotics and aerospace missions [23][27].
(2) Complexity Based on its level of feedback, a system may be considered simple, intermediate, or complex. Simple systems comprise control interface s such as displays for communication, word processing, web browsing, etc., where feedback is primarily visual [32]. Intermediate control interface are interfaces that require more complex interaction with the user, such as a wheelchair, where the controller needs to be aware of the surroundings while interacting with the control interface. Complex control interfaces require a higher level of control such as prosthetic limbs moving in 3D space, exoskeletons, etc." Here, the user not only has to focus on the device and their surroundings, but also has to engage with multisensory feedback from their control interface.
(3) BCI can also be categorized based on the control interface input, that is, discrete or continuous control input. Here discrete input may be received as discrete states from mental imagery or an evoked response representing discrete states received at discrete time points. Continuous input may be updated in real-time describing the relative position or movement in 2D or 3D space.

Table 1. Table showing the control interface types and the respective inputs and outputs to the control interface.

Control Interface	Input (logical)	Output (Semantic)
SSxEP (Visual, Somatosensory)	n discrete states	m commands ($m \geq n$)
mu-rhythm	Analog control	Analog/Digital control
Mental Imagery	n discrete states	m commands ($m \geq n$)
P300	n discrete states	m commands ($m \geq n$)
xEP (Visual, Acoustic, Somatosensory)	n discrete states	m commands ($m \geq n$)

In Table 1, the n discrete states are the specific input states, with the output representing the number of commands. This is the logical to semantic symbol mapping previously described.

The current body of research is replete with important studies on the various aspects of BCI control interface. However, what is currently lacking is a coherent, generally applicable model of a BCI control interface. Such a model would facilitate research across the entire spectrum of BCI research.

Shih, Krusienski, and Wolpaw state: 'BCI system consists of four sequential components: (1) signal acquisition, (2) feature extraction, (3) feature translation, and (4) device output. These four components are controlled by an operating protocol that defines the onset and timing of operation, the details of signal processing, the nature of the device commands, and the oversight of performance'. [25] This description of BCI components is relevant to developing an effective functional model for BCI. These components are addressed in the P2731 working group functional model.

The Shih, Krasinski, and Wolpaw description is consistent with the functional model being proposed by the P2731 working group. The transducer is responsible for feature extraction and sends logical symbols to the Control Interface, specifically the encoder. The control interface's encoder then encodes those symbols. Feedback is related to device output. These fundamentals are true, regardless of the specific implementation of BCI. It is these general concepts that can form a widely applicable functional model for BCI.

3. Description of the model

In general, no direct processing of brain signals occurs in a control interface. Rather, the module implements encoding strategies to convert sequences of logical symbols (e.g. the output of a classifier) into semantic symbols (e.g. the selection of a character in a spelling application). This is how the classical P300 Speller works [26]: each pair of rows and columns (the logical symbols, or the labels of a classifier) corresponds to a semantic symbol (the characters of the English alphabet, the digits, and the space char). The key to note, however, is that no direct processing occurs in the control interface. Brain signals are first classified as logical symbols by the transducer. Then, that transducer output is processed by the control interface.

The control interface is characterized by the input and output interfaces, which are represented by the logical and semantic alphabets, respectively. One can then easily replace a control interface provided the new control interface can operate with the original alphabets. In the following subsections, the components of a control interface are described.

3.1. Encoder

The purpose of an encoder is to translate signals into a form usable by a controller, for example, a physical or virtual actuator. This process is how a user of a BCI encodes their intentions. The encoder, within the control interface implements encoding strategies to convert sequences of logical symbols (e.g. the output of a classifier within the transducer) into semantic symbols (e.g. the selection of a character in a spelling application). This is how the classical P300 Speller works [26]: each entry in a grid of rows and columns (the logical symbols or the classifier labels) corresponds to a semantic symbol (i.e. a digit or a character of the English alphabet). Encoders, as the name suggests, encode incoming signals into a symbolism that is appropriate for the specific application.

In principle, any neurological signal can be encoded into symbolism. Electrical signals detected from the scalp are the most common. However, this is more due to pragmatic considerations than for scientific reasons. It is less intrusive and less expensive to utilize EEG to detect brain activity than other signals, such as fMRI.

A few publications simply refer to an encoder, with the decoder being implied. One goal of any encoder is to be able to identify the sensory input from associated neural spike patterns [10]. There are a wide range of BCI encoders [28]. The model being developed by the P2731 working group provides a general overview of the encoder as part of the control interface.

Given the purpose of an encoder, improving the recognition of neural patterns is an important aspect of encoder design. Concurrent with improving pattern recognition is the integration of machine learning and BCI encoding [24]. Machine learning is an effective tool for improving signal classifications. Of particular research interest has been ensuring that BCI encoding is not overly coupled to a specific user and is instead generalizable [29]. This phenomenon is often referred to as subject invariance [23,30]. This simply means that the encoding process must be applicable, regardless of the specific user.

3.2. Feedback

Feedback is central to any control interface. Feedback comes in many forms. As one example, neural amplifiers typically utilize two seperate feedback path structures to realize a high-pass filter [28]. This is accomplished with two subthreshold-biased transistors or with two diode-connected transistors. This is related to the complexity or level of feedback, that is, simple, intermediate, and complex. The variation between simple, intermediate, and complex was previously described.

It is necessary for the control interface to communicate with the transducer, as well as receive communication from the transducer. The communication from the control interface to the transducer is provided by feedback from the control interface.

Feedback is also provided by the control interface to the user depending also on the input received by the control interface from the transducer (TR). The control interface can receive control signals from two different TR elements: from a classifier and/or from a regressor. This feedback is essential to a fully functional BCI. Without feedback, it is difficult to modify actions to achieve a given goal. That modification can be the user modifying, or other portions of the BCI. In either case, feedback is required for meaningful modifications.

In one implementation, a digital message is received and can be processed (e.g. decoded), as shown in Figure 2, which describes an SSVEP-based BCI during a free-mode session. The elements of the FM that are inactive during it are grayed, while those in green are active only before the session (e.g. to load weights or train classifiers).

In another implementation, instead, the control interface may be responsible to also generate the logical symbol. In [31], in fact, where a 2-D cursor control is achieved by means of the modulation of the mu-rhythm, a trial is completed and a selection is performed when a cursor hits a target on a 2-D screen within a predefined time, otherwise the selection is aborted. It is then the control interface that can identify when this event occurs, because

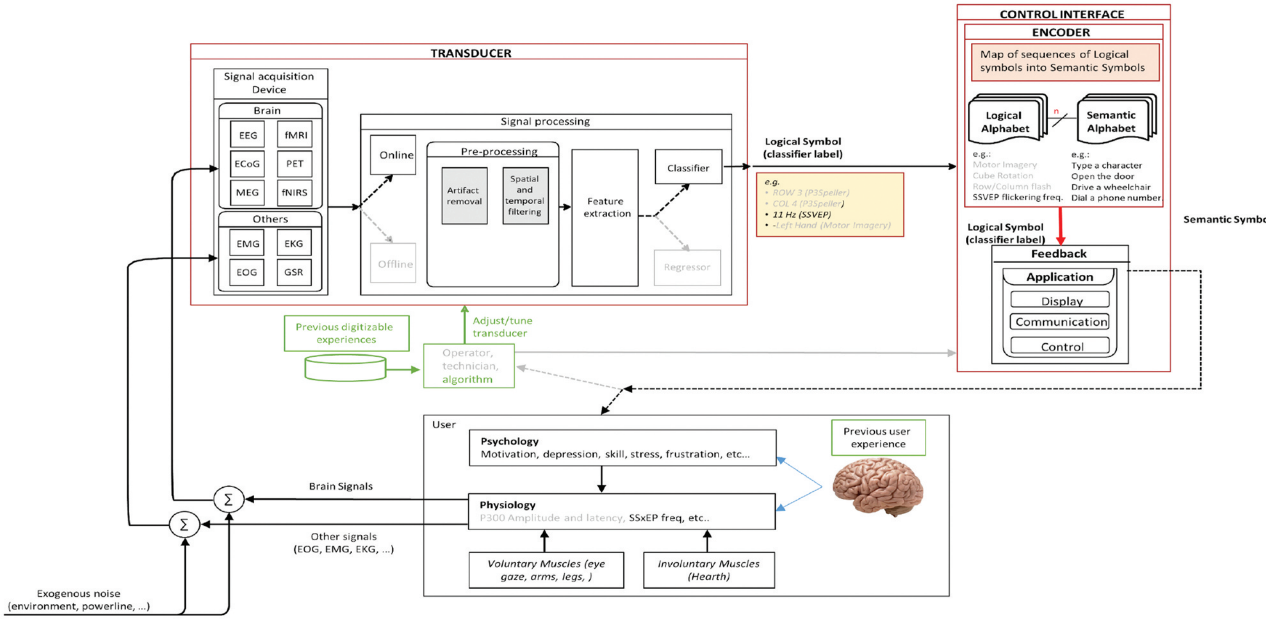

Figure 2. SSVEP session.

the TR is unaware of the internal state of the control interface. In Figure 3 a mu-rhythm based BCI during a free-mode session is described with gray and green elements that indicate those inactive or active only before the beginning of the session.

Figure 2 provides insight into how the control interface is interacting with the other relevant components. These other components include neurophysiology and subject psychology as well as engineering components, such as the transducer. Each of these components is

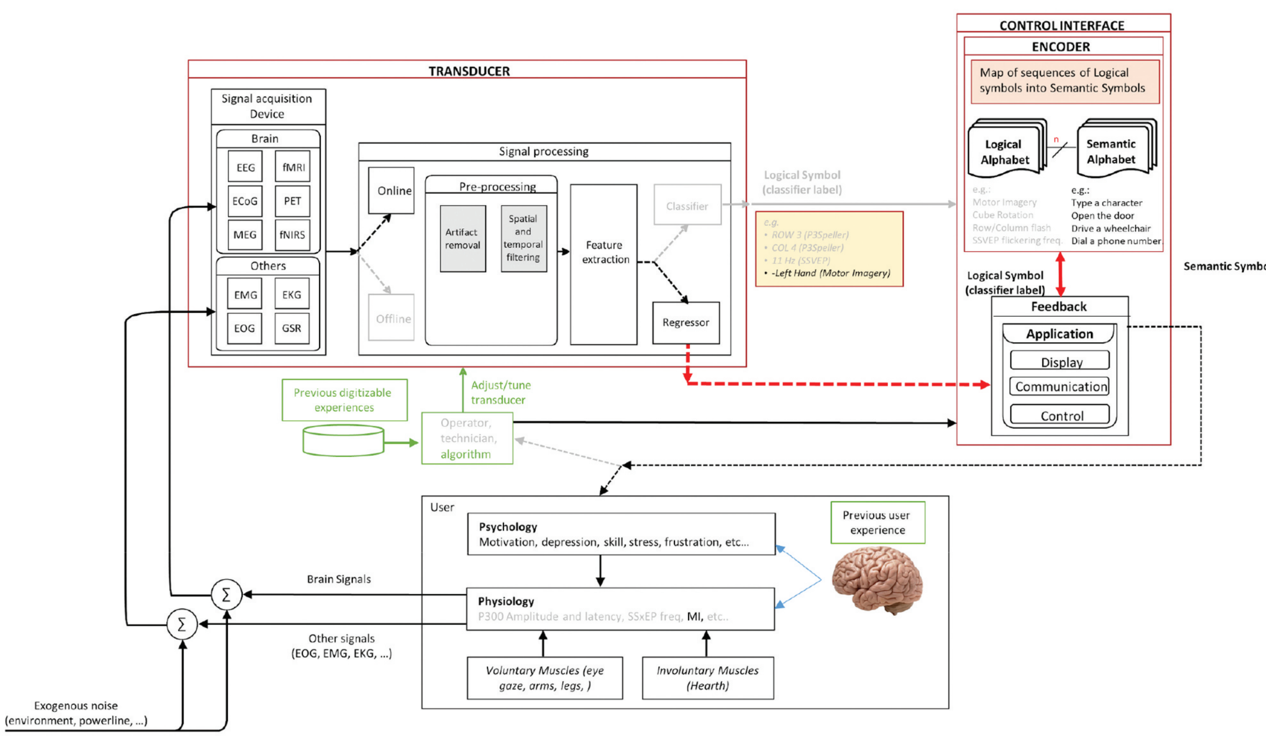

Figure 3. Mu-rhythm.

described in one of the other papers in this special issue. While the focus of the current paper is on the control interface, Figure 2 should provide insight into how that component is integrated into the entirety of BCI.

4. Application of the model

It has been demonstrated [29] that the adoption of different encodings along with different control interfaces affects the performances of BCIs. This is often a cause of confusion because control interface does not directly handle brain signals whereas transducers do. This suggests that if one wants to demonstrate the ability of a BCI system to correctly identify brain patterns, the performance should be evaluated at the output of the transducer (e.g. at the classifier output), while the whole system should be evaluated after the control interface.

It must be realized that the adoption of a more or less efficient control interface could affect the psychological state of the user (e.g. increase motivation or frustration). This can further affect the SNR (Signal-to-Noise Ratio) of the brain patterns to be detected and then the performance of the transducers (e.g. accuracy of the classifiers). This is also one of the reasons why psychological and physiological elements are included in the functional model. While the number and diversity of public datasets increases, it can be possible to model and profile users to provide strategies to optimize BCI performances according to users' psycho-physiological state.

A key requirement to applying the current model is clear and objective evaluation criteria of performance. Such criteria must recognize the practical control interface function within BCI – user interaction cycle. The control interface is the clear and tangible evidence of system responses as perceived by the user. Hence, a user-centered approach should supplement any existing performance criteria to be used. To illustrate this point, the reader may wish to examine an example from any BCI application domain, for example, assistive technology. If the BCI is used to control a mobility assistive device, the control interface signals to the device motors are the first signs of the outcomes from the internal BCI processes. This is also the first encounter the user will have with the results of the various parts of the model. The impact on the user is substantial, hence performance criteria would need to consider the well-being of the user in this context. The new IEEE 7010 standard [33] can provide a basis for best practices in developing objective performance criteria that address well-being. Implications and encapsulate the essence of the control interface and BCI functions from a user perspective within each specific domain in which they are utilized.

5. Conclusions

Brain–computer interface research requires a generally applicable functional model to facilitate communication between researchers. Therefore, standardizing the functional model is integral to BCI research. Furthermore, the control interface is an important part of the functional model. The control interface provides the fundamental mechanism for communication within the BCI.

The control interface is responsible for encoding incoming signals into symbols that are useful to the application. Feedback is also a critical component of any control interface. The control interface proposed as part of the IEEE P2731 working groups functional model is intended to be universally applicable. For that reason, it is intentionally not specifically tied to a particular BCI application.

The most obvious area for future work is for the IEEE P2731 working group to continue to refine both its functional model and its glossary. However, there are additional areas of research suggested by this current paper. As one example, applying this universal control interface model to specific BCI applications. Such specific applications would either validate the universality of the model or point to specific areas of the model that would benefit from revision.

Acknowledgments

While this paper is the work of a subset of the IEEE P2731 working group, it must be noted that the paper is the culmination of the work of the entire IEEE P2731 working group. While not all members of that working group are listed as authors, their work provided the foundation for this paper.

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