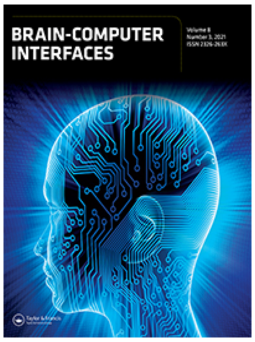

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ARTICLE

A Functional BCI Model by the P2731 Working Group: Transducer

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ABSTRACT
A Brain-Computer Interface (BCI) can be considered as a technology that allows for alternative means of communication between humans and their environment using thoughts and intentions. The structure of this interface is composed of various stages, beginning with the acquisition of the brain signals, followed by several processing stages, and leading to the generation of feedback signals. The development of a BCI system involves a diverse set of expertise in order to produce a unique environment for continuous innovations. However, such diversity in technical background and expertise may lead to confusion in the terminology used by the community. As such, the IEEE P2731 WG has been tasked with the development of a functional model to facilitate the understanding of a BCI system. In this paper, we focus on the description of the functional elements that belong to the transducer stage of a BCI.

ARTICLE HISTORY
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KEYWORDS
Brain-Computer Interface; Functional Model; BCI Description; BCI Signal Processing; IEEE P2731

1. Introduction

Brain-Computer Interface (BCI), as the key concept of neurotechnologies, has drawn significant attention during the last decade. Efforts like BNCI 2020 [1] and BRAIN [2] have been initiated to better understand how the human brain works, and consequently apply its inner functional principles to a variety of technical areas such as neuroprosthetics. Efficient and accurate implementation of BCI technology not only impacts its clinical applications, but could also have significant implications in people's everyday life. In fact, the diverse set of applications of BCIs include sports [3], entertainment [4], home automation [5], marketing [6], and even automated work-performance assessment [7].

The development of BCIs typically requires a multidisciplinary research team consisting of experts in neuroscience, engineering, biology, psychology, etc. Although, such intellectual diversity creates a fertile ground for innovation, different perspectives of BCI among these experts along with lack of standard vocabularies, and data formats could cause challenging issues and obstacles when developing new solutions, reproducing peer reviewed published results or aggregating data to produce comprehensive models. Some of these issues are not primarily related to BCI. They also appear in other disciplines where data takes a central role in the analysis and often involves sophisticated algorithms and machine learning [8]. For example, aside from data considerations, in neuroimaging, reproducibility becomes more relevant as human factors must also be considered alongside other technical issues [9].

Reproducibility of experimental results where researchers can conduct (as a way of conducting) further experiments based on previously established results, is of paramount importance in advancing scientific work [10]. Reproducibility issues in BCI- related research slow the progress and force researchers to recreate tools, datasets, and even algorithms, resulting in what is known as replication or reproducibility crisis [11]. The main reason behind this crisis is the lack of standardized data format, terminology, and missing meta-data during research and publication of the results. To alleviate this problem and support the progress of BCI-related science along with its corresponding engineering applications, the IEEE P2731 Working Group has been tasked with the development of a Functional Model (FM) that describes a generic BCI system. The FM can be used as a central point of reference by researchers with diverse expertise. The proposed FM is structured in specialized modules as shown in Figure 1. This is an extension of the FM presented in [12]. The model outlines different stages of the BCI process and describes each stage in terms of its functionality. In this paper, we focus on the transducer module which is in charge of acquiring brain signals and processing them

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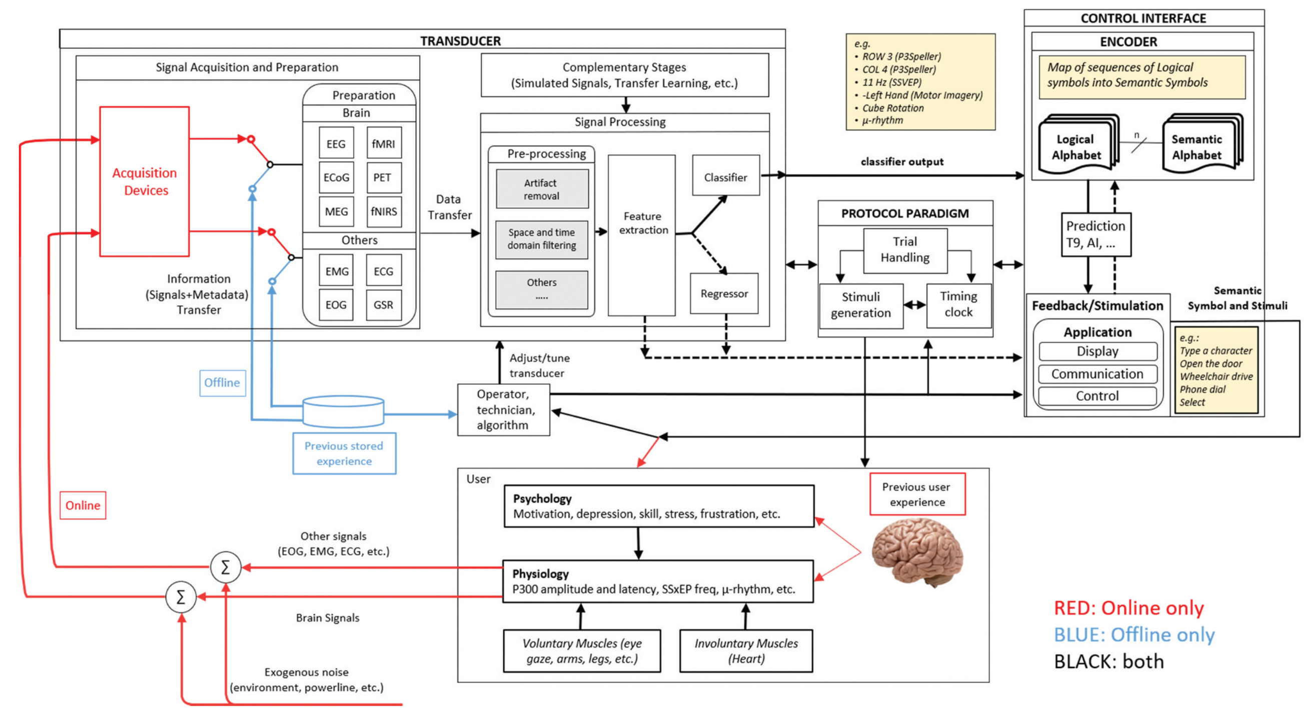

Figure 1. Block diagram of the Functional Model proposed by the IEEE P2731 working group.

according to a BCI schema i.e., online or offline. The objective of the transducer is to produce logical symbols that can be used to establish actions through the control interface to influence the user environment. The resulting information can also be used as feedback to the same user in a closed-loop approach.

This paper is organized as follows. Section II provides a review of the literature. A detailed description of the proposed transducer model and its components is presented in Section III. Section IV discusses the application of the model by describing several published BCI studies. Finally, conclusions are provided in Section V.

2. Literature review

The general framework of a BCI can be observed from two perspectives: training and execution. The first perspective focuses on training a given user to employ the system, and training the system so that it can understand the user's brain activity. The second perspective, however, involves running designed or learned automatic procedures so that the interface can work along with the user, preferably in real-time. Similarly, a BCI system can be configured to work either in an online or offline mode [13]. The online mode implies that the device will be running and computing outputs at the same time as the user is utilizing the device. The offline mode refers to the steps that take place when the data is being recorded for further processing or analysis. The offline mode may occur without providing any feedback to the user. The acquired data from the offline mode is used to calibrate the system before configuring a BCI in the online mode. In either mode, it is possible to find common processing elements that will take part in the data processing flow of the system. Moreover, there is a complementary mutual element that relies on a set of fixed instructions which users must follow to fulfill the specific experimental routines. These instructions involve preparation processes for arranging the data to be analyzed by the system algorithms. In the remainder of this section, we briefly review prior studies that have proposed frameworks to describe the operation of BCIs.

One of the first attempts to define a BCI functional model was made by Mason and Birch [14]. The model essentially described a static approach that included six components: user, electrodes, amplifier, feature extractor, feature translator, and control interface. These components may be combined into three main modules: BCI control, control interface, and device controller. The first module i.e., BCI control, is in charge of acquiring and processing the brain signals. Later on, Quitadamo et al. [15] showed that the structure of the transducer could be extended to dynamic and reported the main timing issues of five different BCI paradigms (P300, mu-rhythm, SSxEP, Slow Cortical Potential and mental imagery) using class and sequence Unified Modeling Language (UML) diagrams.

More recently, Nam et al. [13] proposed a BCI framework consisting of four main modules. The first one (Signal Acquisition) involves capturing brain signals through a given neuroimaging technique. The second module (Signal Processing) depends on the BCI mode that is being used i.e. online or offline, and includes sub modules as preprocessing, feature extraction and classification. The third module (Feedback) generates feedback signals to the user based on a specific BCI application. Finally, the subject/user that is utilizing the system is considered as the fourth module. This framework is similar to the workflow that Wolpaw [16] mentioned when describing the operation of a BCI. Such workflows are structured around three main processes: signal acquisition, feature extraction, and feature translation. Authors in He et al. [17] define four components: signal acquisition, feature extraction, feature translation, device output commands or neurofeedback training paradigm. The authors mention that a BCI also implies an operating protocol which establishes details of implementation or deployment.

Kosmyna [18], on the other hand, described Electroencephalography (EEG) based BCIs according to a conceptual space based on four axes (temporal, spatial, content, and medium) and organized in nine sub axes: interface adaption, decision about execution, command initiative, neural mechanism, input type, pragmatism, interaction task, multimodality, and representation space. Although originally conceived for EEG based BCIs, the design space can be extended to other types of BCI. However, the proposed abstraction does not explicitly define processing stages. Instead, it focuses on qualitative categorizations of features in a BCI system. Vasiljevic [19] also presents a general model for EEG-based BCI games including three main processes: acquisition, implementation, and feedback. While the acquisition and feedback processes are similar to those described in previous frameworks, the implementation refers to three submodules: (1) a control interface that includes signal pre-processing, feature extraction, feature selection, and classification, (2) a game logic which considers the BCI control mechanics, and (3) a virtual interface where the neurofeedback interface and stimuli generator reside.

BCI frameworks or workflow descriptions commonly define the signal acquisition as the first stage of the system followed by signal processing techniques as the steps prior to the application interface. Functionally speaking, this implies that once the brain signals have been acquired, processes will transform them into a set of representations that could be used later to control devices. The acquisition process described by previous studies implies the usage of different techniques that can be categorized according to their invasiveness or their measured physical properties [20]. The acquired signals reflect the internal state or activity of the brain with a certain degree of reliability due to various physical constraints. Some acquisition techniques provide signals with good time resolution e.g., EEG and Electrocorticography (ECoG), while others offer better spatial details e.g., functional Magnetic Resonance Imaging (fMRI). The trade-off between techniques often relies on identifying priorities according to the BCI applications. For example, BCIs that focus on specific regions of the brain require fMRI as in [21], but those that focus on mobility employ techniques such as EEG [22]. The data processing steps that occur after signal acquisition often include data cleaning algorithms to remove noise or undesired signals from the samples. Current trends on BCI development also consider machine learning based feature extraction and classification methods to better allow the interpretation of the pre-processed data [23]. These and other concepts will be covered more extensively in the following sections.

The proposed Functional Model that is being considered under IEEE P2731 is similar to the framework in Nam et al. [13]; however, it also includes physiological and psychological aspects as well as data sharing considerations. These aspects make the proposed FM more informative by providing details that were not contemplated previously but are undoubtedly required for a complete description of a BCI system. In the following section, the details of the transducer module are described.

3. Description of the transducer model

The Transducer is the only module of the FM that is responsible for processing brain signals which represent neurophysiological activities and the psychological state of the user. Structurally, input data to this module comes from the online data acquisition or offline data retrieval. Interactions with the Transducer module can be traced to: (i) the received configuration or tuning by an external operator, technician or algorithm, (ii) the Control Interface block, and (iii) the Protocol Paradigm block. Furthermore, the internal structure of the transducer is composed of two main and one complementary stages (see Figure 2). The first stage is Signal Acquisition and Preparation (SA&P) including the following two steps: neural data recording/acquisition and data preparation for further processing. The next stage is Signal Processing (SP) which consists of three sub-stages: (i) pre-processing where artifacts are removed from the recorded data and filtering processes are applied (ii) feature extraction where meaningful neural information is extracted

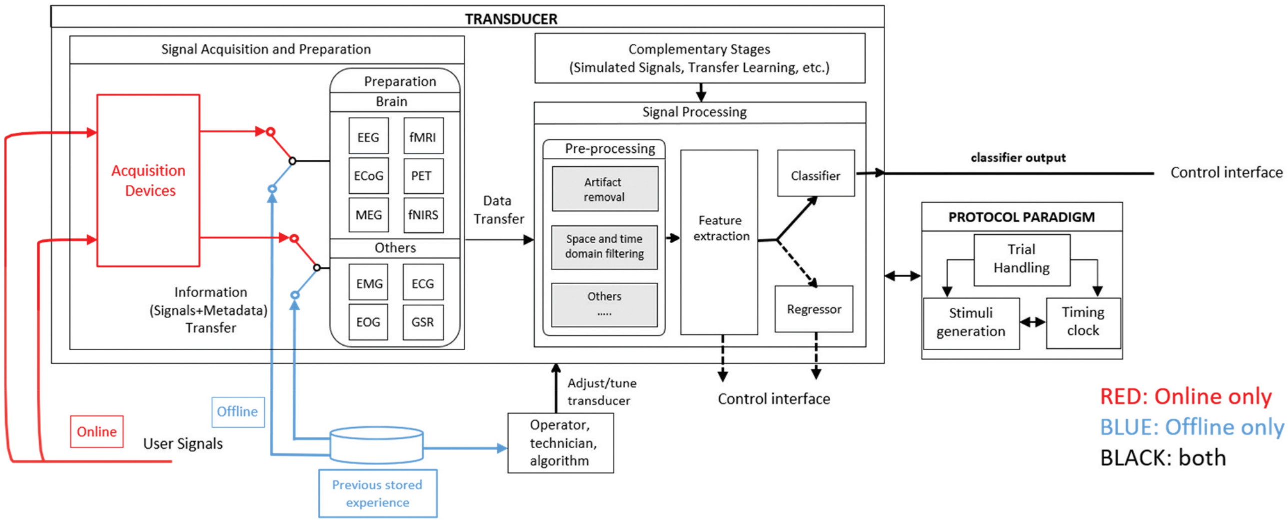

Figure 2. Internal structure of the Transducer module.

from the recorded data and (iii) a classification or regression sub-stage where a user's intention is decoded from the extracted features. In addition, the complementary block includes different optional techniques that can be used in parallel to enhance the BCI performance by using paradigms such as Transfer Learning or Signal Simulation. In the following subsections we further describe each of the stages that were mentioned above.

3.1. Signal acquisition and preparation

3.1.1. Acquisition devices

There are several techniques to acquire brain signals from the user. They are often categorized by their invasiveness, spatial resolution, temporal resolution, direct/indirect measurement, involved cost, and portability [20,24,25]. BCIs can also be characterized based on the features of each acquisition technique. For example, BCIs employed for improving performance in sports require portability as in [26], and BCIs that are intended to establish functional connectivity may use high spatial resolution techniques "[27] or relatively high density", without the period. low-cost techniques with specialized algorithms [28]. Considering the signals' blocks that are included in the Preparation step of the SA&P process, we will now summarize acquisition techniques in four categories: invasive, noninvasive, hybrid and other signals.

3.1.2. Invasive

These are neuroimaging techniques in which sensors are placed directly over the brain tissues [29]. Invasive methods require an opening of the scalp to place the sensors [30]. Generally, this is done through surgery or procedures such as machine implantation or needle insertion to a specific location in the brain [31]. Some examples are: ECoG [32] and N1 chips [33]. Invasive methods like ECoG provide a great spatial and temporal resolution (1 mm and 5 ms as presented in [34]); however, they require expensive surgery with some risks involved.

3.1.3. Non-Invasive

Unlike invasive methods, noninvasive techniques involve sensors that are placed over the scalp; and therefore, they do not require a surgical procedure to acquire brain signals [30]. Some examples of non-invasive methods are the electroencephalography (EEG) which measures electrical activity, and the magnetoencephalography (MEG) which measures electromagnetic activity of the brain [35]. Other methods such as functional magnetic resonance imaging (fMRI), functional near infrared spectroscopy (fNIRS) and positron emission tomography (PET) are also non-invasive; however, they indirectly measure brain function by capturing brain metabolism or hemodynamics [36].

Non-invasive methods like EEG generally have a high temporal resolution, but lower compared to invasive techniques i.e., 50 ms vs. [3 ms – 5 ms] according to [34]. In addition, their spatial resolution is lower [20] i.e., 10 mm vs. [0.05 mm – 1 mm] as stated in [35]. Nevertheless, non-invasive techniques are also significantly cheaper and mostly portable [36]. An important point to consider in noninvasive methods is the matching impedance of the electrodes placed over the scalp [37]. For EEG signals acquisition, it is advisable to have an impedance of less than 5 K ohms [38]. This will ensure better acquisition and identification of the brain activity signals from the noise.

3.1.4. Hybrid acquisition

Hybrid acquisition refers to the process of using different techniques simultaneously in order to improve the quality of the outputs. This is due to the fact that techniques such as fMRI, ECoG and EEG can result in correlated brain signals [39]. For example, authors in [40,41] proposed to use EEG and fNIRS to enhance classification accuracy of mental and motor tasks. Similarly, it has been proposed in [42] to complement fNIRS with fMRI; however, this strategy could cause portability issues or higher costs.

3.1.5. Other signals

As observed in Figure 2, other signals can also be used to complement the BCI workflow. For example, authors in [43] used correlations between EMG (electromyography) and EEG to reject EEG channels that are contaminated with artifacts. Similarly, in [44] ECG (electrocardiography) signals were employed in combination to EEG to improve emotion recognition. In addition, authors in [45] proposed to use electrooculography (EOG) as a complementary input to develop hybrid BCIs (hBCI). Finally, GSR (Galvanic Skin Response) signals were considered in [46] to understand the effects of using BCI for gaming.

3.1.6. Information transfer

Once data is acquired or retrieved from a database, it should be transferred to the computing elements for further processing. This information not only includes brain signals, but also a combination of meta-data e.g., information regarding different technical details such as the sampling frequency, battery level or even the sensor contact quality[1]. While the process of transferring this information is typically through wired connections, ease-of-use for extended or long-term recordings of brain signals has initiated interest in wireless data communication from the signal acquisition module. Recent advancements in wearable technology offer an alternative to wired sensors that are mostly used in clinical settings [47–49]. Although, there are still many challenges facing reliable commercial use of BCI systems, progress in low power microelectronics as well as ongoing standardization efforts[2] could lead to further utilization of wireless technologies.

The adoption of standard wireless interfaces for signal acquisition not only enhances the usability of the system by alleviating the obstructive wired connections, but also facilitates the development of platforms that further integrate the brain with other physiological signals. Sensors that capture other physiological signals are generally developed by different manufacturers; therefore, usage of standard communication protocols will also be helpful in resolving potential interoperability issues. Common standards such as Bluetooth and Zigbee are frequently used in wireless sensor devices[3]. For example, some commercial BCI products[4] like NeuroSky and EPOC X already use Bluetooth in Low Energy mode (BLE). However, as the unique characteristics of the propagation media (i.e. human body/scalp tissues or surface) is not typically considered in BLE and Zigbee, wireless standards developed primarily for wearable or implantable devices will be more appropriate for use in the acquisition modules of the BCI transducers. Two such standards are the IEEE802.15.4 j Medical Body Area Networks and IEEE802.15.6 Body Area Networks.

The frequency bands and variety of physical and medium access layers (PHY/MAC) supported by the latter standard (i.e. IEEE802.15.6) could provide sufficient transmission capacity for higher data rate applications such as ECoG [50]. Specifically, the Ultra WideBand (UWB) physical layer in IEEE802.15.6 can support high data rate transmissions required for dense spatiotemporal sampling of the brain neural activity. Nevertheless, this would only apply to non-invasive BCI applications as there are currently no standards for UWB implant communication. Accurate signal characterization and channel modeling will be helpful to determine the best wireless transmission technologies for the desired BCI applications.

3.1.7. Data preparation

We define data preparation as any method or process that arranges raw transferred data into useful batches and property fields. Some examples of this preparation are: epoching and simple data fragmentation. Epoching is defined as the process of taking time or spatiotemporal-based windows from the continuous neural data. This preparation step is crucial for estimating unbiased functional connectivity [51]. In addition, it has been shown that the

[1] Extracted as an example from the Emotiv Documentation available in https://emotiv.gitbook.io/cortexapi/data-subscription

[2] https://standards.ieee.org/industry-connections/neurotechnologies-for-brain-machine-interfacing.html

[3] IEEE Standards 802.15.1 and 802.15.4

[4] Commercial products mentioned in this paper are merely intended to foster understanding. Their identifcationdoes not imply recommendation or endorsement by the respective organizations of the authors.

length of epochs affects compressive sensing approaches to EEG signal compression and reconstructions [52]. Moreover, epochs are also related to the time reference periods in which signal processing algorithms are executed in compliance with the Protocol Paradigm definition as presented in [53]. Simple data fragmentation process, on the other hand, is defined as the segmentation of neural data and meta-data into different memory arrays.

3.2. Signal processing

Once the appropriate signals are acquired in the first stage, it is essential to identify whether the BCI will be completely online or the data will be used for offline calibration first [54]. In order to overcome the problem of subject-variability, it is a common practice among BCI researchers to calibrate the system offline first. Then, once acceptable performance is achieved, the system mode operation is switched to online [55]. Some of the critical factors to be considered for online BCI are [56]:

- Real-time feedback
- Performance measure in information transfer rate, number of successful trials, accuracy of correctly detecting commands, etc.
- User satisfaction on usefulness, fatigue/exhaustion, safety, control, comfort, etc.

The raw signals acquired in the acquisition stage are not immediately ready to be used for BCI. They do not usually come with the required sampling rate, signal quality and commonly have multiple kinds of artifacts [57–60]. It is therefore important to process them before moving to the next stage. There are two main steps involved in signal processing: pre-processing and feature extraction.

3.2.1. Pre-processing

This step generally involves basic signal processing algorithms that enable sharing standardized data sets among the community. This includes:

- Down-sampling of brain signals,
- Re-referencing of the data set to common average (common for EEG and fNIRS signals) [61],
- Band-pass filtering of data (also applies mostly in EEG [62] and fNIRS [63]).

While the existence of a standard pre-processing pipeline for EEG signal processing has been disputed in [64], there has been efforts on proposing standard pipelines as specified in [65] and [66]. However, it should be emphasized that these studies only focus on EEG data and not on neural data for BCI in a generic manner. Nevertheless, there are some commonly used pre-processing steps related to artifact removal and space-time domain filtering [17] which can be applied sequentially if needed. Furthermore, other methods or techniques may also be used to enhance the quality of the results or the data that the system is using. Therefore, instead of a sequence, Figure 2 includes a list of pre-processing tasks.

3.2.1.1. Artifacts Removal. Once pre-processing has been performed, it is crucial to remove non relevant information from the brain signals. These non-relevant signals are generally known as 'noise' or 'artifacts'. Artifacts are usually added to the main signal by sources in the environment (e.g. nearby power lines or light sources) [67], or physiology (e.g. muscles, eye blink). They can also be originated from faulty devices (e.g. broken channels sources, drop-in signals) [59,68]. Artifacts significantly reduce the signal-to-noise ratio (SNR). A poor SNR results in poor BCI performance; therefore, it is crucial to remove these artifacts from the recorded signal. Some of the commonly used steps to reduce artifacts are ([68], and [69]):

- Removing noisy channels
- Interpolating removed channels
- Detection and removal of random peaks/noise in the signals based on power spectrum, standard deviation, z-score, etc.
- Detection and removal of eye blink
- Applying advanced artifact removal techniques such as:
  - Artifacts subspace removal (ASR) [70]
  - Independent component analysis (ICA) [71]
  - Dipole fitting [72]

3.2.1.2. Space and time domain filtering. Based on the type of the acquisition device or hybrid modality that is used, a given BCI may require to employ either spatial or temporal filtering, or both. The main reason for using such filters is related to the specific features of the acquisition technique. For example, when using low-spatial resolution techniques such as EEG, it is common to require spatial filtering such as Common Spatial Patterns (CSP) [73]. Considering that neural data can be characterized through different temporal features, spatial filtering can also be complemented with temporal filtering techniques such as Common Spatial and Temporal Patterns as proposed in (CSP-CTP) [74].

3.2.2. Feature extraction stage

The cleaned signals obtained after the artifacts removal stage can be further processed to extract the required bio-markers or features for specific tasks. Different BCI applications require different features that need to be computed or identified. Feature extraction could be based on time-series information, time-frequency or a combination of both as follows:

3.2.2.1. Time-series features. The brain reacts almost deterministically to certain stimuli when they are provided in a very structured way. These stimuli produce unique bio markers in time-series signals such as EEG. The corresponding biomarkers/features are easy to extract for a given time-locked information. Examples of such biomarkers found in the EEG signals are event-related potential (ERP) components: P100, P200, P300, N100, the error-related negativity (ERN), N200, N400, etc. [75].

3.2.2.2. Time-frequency features/spatial features. Time-frequency features are produced in a time-locked stimulus but only visible or interpretable in the frequency domain [76]. Researchers need to convert a given time-series into the frequency domain or the preferred time-frequency domain to extract such features. Examples of such biomarkers include Synchronization/Desynchronization of power bands (delta, theta, alpha, and beta) [77], steady-state visually evoked potentials (SSVEP) [78], and sensorimotor rhythm (SMR) [54]. It is also possible to use adaptive autoregressive (AAR) [79] parameters as characteristics of the signals when representing the frequency domain. As for spatial features, a frequently used feature extractor is the Common Spatial Patterns algorithm, which can be seen as a spatial filtering procedure to maximize the variance between two classes [80,81]. While CSP has been used in works related to motor intention as in [82], other researchers have proposed the combination between spatial and temporal features as in [83].

3.2.2.3. Blind source separation (BSS). In addition to time-series and time-frequency domain feature extraction, features can also be extracted using blind source separation techniques [84]. These techniques are generally very useful for noninvasive signals to identify brain regions as a feature of BCI tasks. Some of the most commonly used BSS methods are Principal Component Analysis (PCA) [85] and Independent Component Analysis (ICA) [71]. Both of these methods are able to point toward the organization of sources of the signal. For example, for a motor imagery BCI task, BSS methods are able to identify the left or right motor regions during the task as a source of the main feature. Dipole fitting is also most commonly used together with the BSS method to increase the confidence level in the identified feature.

Once features have been extracted, it is typical to implement a process of feature selection by which only relevant or useful features will be passed on to the next stage. This process by itself follows the criteria of the feature extraction method. In other words, the technique that will be used for selecting features depends on the process that was used for extracting them.

3.2.3. Classification and regression stage

Once the desired features have been extracted and selected then a natural step is to feed the Control Interface to provide the feedback to the user. This can be mainly done in two different ways:

(1) Through the classifier output i.e. by providing a label (Logical Symbol) which represents one of the possible detectable BCI user mental states. This would depend on the used paradigm (e.g. an evoked response, motor imagery, etc.), and the feedback is provided at the end of a trial.
(2) Through a regressor which usually provides a continuous control signal used by the Control Interface as in the case of a cursor controlled by the mu-rhythm. This control signal can also be multidimensional as described in [78].

Classification can be achieved by a variety of methods that are suitable for specific tasks. Some of the most commonly used classification methods in BCI are:

3.2.3.1. Linear classifiers. Use of linear classifiers is widespread in BCI research. This method assumes linear separability in the brain signals. In fact, there are several such signals where linear separability exists. As a result, linear classifiers could easily achieve high performance. In addition, linear classifiers are better understood and more easily explained. However, they are susceptible to noisy information that could be present in the BCI tasks. The examples of linear classifiers used in BCI are Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Regularized Discriminant Analysis (RDA), Logistics Regression (LR), Naive Bayes [23].

3.2.3.2. Non-linear classifiers. Linear classifiers are not always able to perform at an adequate level. For those cases, more advanced non-linear classifiers such as Support Vector Machines (SVM), Random Forest, and Neural Networks [23] can be used. These classifiers have shown significant performance improvement compared to linear classifiers. However, they come with the cost of time and space complexity. Therefore, they are not very suitable for scenarios with limited resources.

3.2.3.3. Deep learning based classifiers. There has been a tremendous interest in deep learning (DL) classification methods in the past several years. DL classifiers have exhibited superior performance in fields such as Computer Vision and Natural Language Processing. These classifiers have also shown high performance for very complex brain data processing and artifact removal. Compared to previously mentioned classifiers, DL-based methods may require a massive amount of data for training and high performance computational resources to achieve optimal implementation. Some of the DL methods commonly used in BCI are Convolution Neural Network (CNN) [86], Recurrent Neural Network (RNN) [87], Deep Belief Networks (DBN) [88], Restricted Boltzmann Machines (RBMs) [89], Autoencoders [90]. A comprehensive review of such classifiers can be found in [91] for EEG, and [92] for fMRI.

3.3. External interactions

3.3.1. Adjusting or tuning transducer parameters

The Transducer may be adjusted or tuned by an operator, technician or an algorithm to enhance its operation toward achieving the best outcome or to prevent failure. For example, considering the role of an operator, if the subject/user is distracted, then the operator may decide to postpone the procedure to a time when the subject can hold his/her attention for the required amount of time. Likewise, if a technician notices any error in the operation, the Transducer could be adjusted to avoid malfunctions. Finally, if an algorithm detects that the previously stored data from the current subject includes a significant number of artifacts, then proper adjustments on the sensitivity setting of the artifact removal process may automatically take place.

3.3.2. Control interface interaction and online/offline considerations

The data flow that characterizes a specific instance of the Transducer depends entirely on the use-case under consideration. Thus, the dashed lines in Figure 2 represent alternative data flows or implementations of the Transducer in a given BCI. For example, authors in [93] used the extracted features as input to the Control Interface that was applied to a computer mouse. Accordingly, the dashed lines in the proposed Transducer model allow this direct connection from the feature extraction to the Control Interface block. Another example can be found in [94], in which the proposed BCI achieves continuous decoding based on regression to allow the user control a desired device.

Furthermore, the blue lines in Figure 2 represent the operation of the Transducer in offline mode where previously recorded signals are used by the BCI. Likewise, the red lines represent the online mode with complete real-time interaction with the user. Despite the complementary nature of online and offline modes and as shown in studies like [95,96], offline oriented studies may also focus on developing the foundation of BCIs that can later work as online [97]. Those studies can also contribute toward developing techniques that may reveal patterns to simplify neural signals classification as in [98].

3.3.3. Protocol paradigm block

Similar to other elements of a BCI, the Transducer must operate according to specific routines which are also followed by the user and the other data processes. These routines make up the Protocol Paradigm which interacts with the transducer to adjust how the processes perform in terms of their timing and epoching. The Protocol Paradigm block not only handles how trials are structured, but also establishes the policy on the type of stimuli and the timing of its generation. This block also provides the appropriate label for the acquired data and the required processing steps that the Transducer must execute.

3.4. Complementary stages

Both signal acquisition and signal processing modules may benefit from simulated signals and transfer learning in some BCI scenarios. For example, Hartmann et al. proposed a generative adversarial network (GAN) as a technique for data augmentation in BCI tasks. This technique can be considered as an application of 'simulated signals' [99]. Also, artifact removal, feature extraction, and classification can be enhanced through the application of Transfer Learning or pre-trained Models as these processes may be initially designed considering previously acquired knowledge using similar data sets.

3.4.1. Simulated signals

In some high performance BCI applications, there is a need for a simulated signal module which has special importance during machine learning training or testing. In those circumstances, the signal acquisition module is replaced by the simulated signal module. The function of the module is to generate the desired brain signals per requirements. Popular methods, such as Generative

Adversarial Network (GAN) can be used to simulate brain signals based on the desired properties, for example, generating more trials for imbalanced classes in error-related negativity for conflict and non-conflict classes [99,100]. These simulated signals are beneficial while working with an online system. They provide additional important information and features required for better performance.

3.4.2. Transfer learning stage

The signal processing, feature extraction, and classification stages are essential for a successful BCI system. However, due to the limitations in the tasks and data, it is not always possible to achieve a good system performance. To overcome these limitations, transfer learning can be applied to enhance the overall system performance by re-tuning the existing weights (which have been learned from similar data sets) according to the new recorded data [101,102]. These pre-trained models can automatically assist in detecting artifacts from the acquired data, enhance feature extraction as well as classification.

4. Application of the functional model

To demonstrate the applicability of the proposed model, we present a brief analysis of several published BCI studies (from the year 2000 to 2021) through the perspective of the proposed FM (see Tables 1 and 2). The different signal acquisition methods used across these research studies not only allow us to highlight their contrasts, but also provide insights on how the presented FM could be used when comparing different BCI systems. For simplicity, the analysis does not include the signal acquisition device. Also, as the transducer module is focused mainly on the signal and data processing, we do not mention the experimental paradigm, devices under control, and the type of feedback offered to the users. These aspects can also be analyzed by considering the other modules of the BCI Functional Model.

The different studies listed in Tables 1 and 2 involve EEG, ECoG, fNIRS, EMG, and fMRI signals. As a result, not all of them apply Artifact Removal steps. This is due to the fact that some Signal Acquisition methods are less sensitive to artifacts than others. As observed, a common step among the listed studies is the frequency filtering process. This is because the energy distribution across multiple frequency bands is typically reflective of the specific brain activities. Moreover, feature extraction methods are especially diverse when considering different acquisition techniques, like fMRI and EEG. Finally, classification procedures are also dependent on the type of the signal and the simplicity of the features. While some of the methods used weighted linear summations, others were based on SVM.

This brief example of the FM applicability can be thought of as a way to further compare different BCI systems designed for the same objective. For instance, consider a researcher that would like to start studying various data processing algorithms that are used for different types of EEG-based BCI focused on mental tasks. The application of the Transducer functional block could allow researchers to quickly build a comprehensive representation of existing systems which can be found through the literature review. The next step after the description would be comparison. That would enable the researcher to identify what spatial and temporal filtering algorithms are frequently used for a particular mental task, and what classifiers seem to be better suited for the desired experiment. Alternatively, consider another researcher who wishes to reproduce the results of a given BCI study. Through the Transducer functional description, it would be possible to easily identify what signal acquisition techniques were used, and what signal processing methods were implemented. Consequently, researchers that utilize the presented functional model allow others to have a clear understanding of the structure they followed to build their BCI.

5. Conclusions

In this paper, we presented the Transducer module of the BCI Functional Model which is being developed by the IEEE P2731 Working Group. The model is intended to describe the structure through which the information is processed in the system.

In general, the input information to a BCI system is obtained through various neuroimaging methods. This information is related to the psychological and physiological activities of the human brain. Previous studies that have focused on the development of a functional model for BCIs, have limited application as they often omit important details of the physiological and psychological aspect, data sharing, and control interfaces. As such, the proposed Transducer module also includes two relatively new mechanisms that are being considered in the BCI community nowadays i.e. simulated or artificially generated signals and transfer learning/pre-trained models.

Finally, we have shown an example of the applicability of the model to compare processing methods of several BCI systems. The comparison, although simple, also provides an example on how the model is applicable to recent as well as earlier BCI systems with different

Table 1. Application of the Transducer conceptualization to different BCI works – Part I.

Publication	Signal Acquisition Method/ Other signals	Signal Processing			
		Artifact Removal	Spatial and Temporal filtering	Feature extraction	Classification or Regression method
Guger et al. [103] (2000)	EEG/EOG[a]	Visual inspection	CSP and FIR filter	Normalized Variances	Linear classifier (Weight vector)
Leuthardt et al. [104] (2004)	ECoG	Not applied	Band pass filtering[b]	Frequency bins	Weighted linear summation
Townsend et al. [105] (2004)	EEG	Visual inspection	FIR filtering and CSP	Normalized Variances	LDA
Choi et al. [106] (2006)	EEG and fMRI	Not applied	Statistical Parametric Mapping and frequency filtering[c]	Band Power	Power difference (t-test)
Shenoy et al. [107] (2007)	ECoG	Not applied	Frequency filtering	Band power features	SVM and LPM[d]
Coyle et al. [108] (2007)	fNIRS	Not applied	Not applied	Not applied	Thresholding
Spüler et al. [109] (2012)	MEG	Not applied	Laplacian derivation and frequency filtering	Power spectrum and r^2 ranking	SVM based
Sorger et al. [110] (2012)	fMRI	Motion correction	Linear trend removal, frequency filtering, and ROI selection	Reference Time Courses and amplitude pattern (β)	Average combination and matching
LaFleur et al. [111] (2013)	EEG	Not applied	Electrode selection and frequency filtering	Time-varying EEG spectral component amplitude	Online integration
Lin et al. [112] (2013)	MEG/EMG[e]	Not applied	Synthetic Aperture Magnetometry and Time- Frequency Map	Extraction: Virtual channels. Selection: GA[f] and Bhattacharyya distance	GA-MLD[g] and Direct Decision Tree Classifier
Rea et al. [113] (2014)	fNIRS/EMG	Wavelet-minimum description length	Statistical analysis and Gaussian low-pass filter	Optical density changes based on Beer-Lambert	LDA
De Venuto et al. [114] (2017)	EEG	Subtraction between normalized EEG signal to fitted polynomial	Frequency filtering	t-RIDE and medically visual inspection features	Decision rules
Zhou et al. [115] (2020)	EEG/EOG	Waveform analysis	Frequency filtering	CCA[h]	Weighted square sum
Cortez et al. [116] (2020)	EEG	Winsorization	Frequency filtering	Feature vector construction	MLP and SVM
Benitez et al. [117] (2020)	fNIRS	Not applied	Frequency filtering and GLM[i] based channel selection	Optical density changes based on Beer-Lambert	GLM

[a]Electrooculography.
[b]This filtering process was implemented before digital quantization.
[c]The authors do not declare explicitly to use a filter, but instead mention to use a specific frequency band (11 Hz – 14 Hz).
[d]Linear Programming Machine.
[e]Electromyography.
[f]Genetic Algorithm.
[g]Genetic Algorithm-based Mahalanobis Linear Distance Classifier.
[h]Canonical Correlation Analysis.
[i]Generalized Linear Model.

Table 2. Application of the Transducer conceptualization to different BCI works – Part II.

		Signal Processing			
Publication	Signal Acquisition Method/ Other signals	Artifact Removal	Spatial and Temporal fil- tering	Feature extraction	Classification or Regres-sion method
Varhesi et al. [118] (2021)	EEG	ICA	Frequency filtering	GCCS[a], CCS[b], RCSP[c]	LDA, SVM, k-NN[d]
Ma et al. [119] (2021)	fNIRS	Not applied	Min-max and Z normalization, FIR and Butterworth filtering	CNN-based	CNN
Mohammadi et al. [120] (2021)	EEG	Channel rejection	Not applied	CWT [e], Autoregressive model, Skewness, Average Derivative, k-means	Linear Support Vector Machine
Stieger et al. [121] (2021)	EEG	Automatic artifact detection	Frequency filtering	Spatial Filtering and Spectrum Estimation	Alpha power translation
Pillette et al. [122] (2021)	EEG/EMG, EOG	Not applied	Spectral and Spatial filtering	Log-transformation of band power information	LDA

[a]Granger Causality Channel Selection.
[b]Correlation-based Channel Selection.
[c]Regularized Common Spatial Pattern.
[d]k-Nearest Neighbors.
[e]Continuous Wavelet Transform.

types of signal acquisition methods. It should be noted that for a more complete description of a BCI, the remaining modules and features of the FM should also be considered. It is our hope that the final version of the functional model developed by the IEEE P2731 Working Group can be adopted and used by researchers when reporting their BCI systems. We expect that the adoption of a standard model will facilitate innovations and advancements in the BCI research.

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