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A Comprehensive Survey of Brain Interface Technology Designs

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Abstract—In this work we present the first comprehensive survey of Brain Interface (BI) technology designs published prior to January 2006. Detailed results from this survey, which was based on the Brain Interface Design Framework proposed by Mason and Birch, are presented and discussed to address the following research questions: (1) which BI technologies are directly comparable, (2) what technology designs exist, (3) which application areas (users, activities and environments) have been targeted in these designs, (4) which design approaches have received little or no research and are possible opportunities for new technology, and (5) how well are designs reported. The results of this work demonstrate that meta-analysis of high-level BI design attributes is possible and informative. The survey also produced a valuable, historical cross-reference where BI technology designers can identify what types of technology have been proposed and by whom.

Keywords—Brain Interface, Brain–Computer Interface, Brain–Machine Interface, Direct Brain Interface, Adaptive Brain Interface, BI, BCI, BMI, DBI, ABI, Comparison, Taxonomy, Models, Framework, Design, Meta-analysis.

GLOSSARY

AT	acronym for assistive (or augmentative) technology
Attribute Sub-Class	sub-category of a design attribute. See Design Attribute. For examples, see Table 2
Assistive Device	the component of a Brain Interface (BI) that interacts directly with objects or people in the environment. For example, a speech synthesizer or an FES-based neuroprosthetic
BI	acronym for Brain Interface
BI AT	acronym for assistive (or augmentative) technology (AT) based on a Brain Interface (BI)
BI Transducer	a component of a Brain Interface that translates a person's brain activity into usable control signals as shown in Fig. 1b–f. Functionally similar to other transducers like joysticks and switches
Bio-recording Technology	the class of equipment (sensors, amplifiers, converters and filters) used to measure a person's brain activity in a BI Transducer
Continuous (fixed reference)	a signal classification; a signal of this class is a sequence of continuous amplitude values relative to a fixed reference value-like the adjustable level produced by an analog potentiometer. See other signal classes: Relative Continuous (no reference), Discrete (...) and Spatial Reference
Control Interface	a component that is added to a BI Transducer that produces a relatively low dimensional output in order to expand the control dimensionality to a level required by an Assistive Device as depicted in Fig. 1c and f. See Table 1 for examples.

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Demonstration System	an experimental system (depicted in Fig. 1e and f) that demonstrates control of a BI Transducer but does not otherwise perform any useful function
Demo Device	a device used to test the controllability of a BI technology in a demonstration system (see Fig. 1e and f). For example, a model vehicle or table-mounted robotic arm
Design Attribute	an attribute of a Brain Interface technology design. See Table 1 for the list of design attributes
Discrete (with 1 NC state)	a signal classification; a signal of this class is a sequence of discrete states including one state that corresponds to the No Control state in the user. See No Control
Discrete (all IC states)	a signal classification; a signal of this class is a sequence of discrete states where all states corresponds to intentional control in the user. See Intentional Control
Discrete (with 1 unknown state)	a signal classification; a signal of this class is a sequence of discrete states where one state (the "unknown" state) is reserved for uncertain classifications
Endogenous Transducer	a BI Transducer design that responds to spontaneous control signals from the user
Exogenous Transducer	a BI Transducer design that responds to control signals evoked from the user using an external stimulator
Feature Extractor	a component of a BI Transducer that translates the input brain signal into a feature vector correlated to a neurological phenomenon. This component is sometimes referred to as noise reduction, filtering, preprocessing or spike detection/sorting
Feature Translator	a component of a BI Transducer that translates the feature vector into a useful control signal. This component is sometimes referred to as a Feature Classifier, Classifier or "decoding function" (or something similar)
Intentional Control	a user state when the user is attempting to affect the output of the Brain Interface
IC	acronym for Intentional Control
Neurological Phenomenon	the phenomenon (or phenomena) used to control a BI Transducer. For example, a P300 response in EEG to an oddball stimulus is a well-studied phenomenon employed in several BI Transducers. Another well-known phenomenon is the increase in neural firing rates measured in microelectrodes as neural activity increases
No Control	a user state when the user is not attempting to affect the output of the Brain Interface. For example, resting, monitoring, thinking, and daydreaming are all possible No Control states
NC	acronym for No Control
Relative Continuous (no reference)	a signal classification; a signal of this class is a sequence of changes to previous amplitude values-like the output of a mouse. See Continuous (fixed reference)
Spatial Reference	a signal classification; a signal of this class is a sequence of 2-D spatial positions (similar to signals output by an eye tracker, a touchscreen or stylus mechanism)

INTRODUCTION

The development of Brain-Interface (BI)[1] technology is a relatively young research field that has grown substantially over the last decade and continues to attract new researchers from multiple disciplines. The aim of this research is to develop an effective and reliable machine interface that is controlled by signals measured directly from a person's brain.[107,125,209]

This paper presents the results of a comprehensive survey of all BI technology designs published prior to January 1, 2006. The first objective of this study was to gather and classify BI technology design information in order to (1) determine which designs are directly comparable and (2) demonstrate that meta-analysis is possible and valuable to the field. The authors were motivated by two factors. First, researchers have identified a critical need for objective methods to compare BI technologies.[108,125,199,208,209] However, direct comparison of technologies assumes individuals can identify which designs are directly comparable. Currently, this does not seem to be the case, as research groups have had difficulty interpreting the myriad of reported technology designs and determining which designs can be compared.[108,199,208] This situation is not surprising given the diversity of perspectives and language used by the professions that comprise this field (including, neuroscience, psychology, engineering, computer science, assistive technology, rehabilitation and other technical and health-care disciplines). As direct, objective comparison is necessary for cross-group validation of findings (the only method to challenge reported performance results), the ability to identify comparable technologies is critical. The second motivating factor was the recent publication of a general framework for high-level BI design and related alterations and extensions.[123,125,129] Prior to its publication, only simple classification schemes had been proposed, each based primarily on the neurological phenomenon used to operate the interface, (e.g., P300 response to an oddball stimulus) or the particular sensor technology used (e.g., EEG, ECoG or implanted microelectrode arrays).[107,200,209] As such, these schemes lacked the necessary depth and breadth to classify the range of design details seen in the literature. The referential models and taxonomy provided in the new framework allowed us to describe all existing BI designs using a common language. Within this context, we were able to identify which technologies existed and which system and subsystem designs could be directly compared. (For readers unfamiliar with this framework, the principle models and taxonomy are reported in the "Review of Design Framework" section.) We want to emphasize that this survey strictly focused on BI technology design and did not incorporate any aspect of performance evaluation.

The second objective of this project was to provide a detailed, historical reference where researchers could (1) determine which design approaches have been proposed, (2) identify design approaches that have received little or no attention, (3) determine which applications areas (users, activities, environments) the existing technology has been designed for, and (4) characterize how well designs have been reported in the literature.

The methods used to conduct this study are detailed in "Methods" Section and the results are presented in "Results and Discussion" Section. Prior to presenting this material, we provide a short review of the design framework that was used as a basis for this survey.

REVIEW OF DESIGN FRAMEWORK

The functional models and taxonomy of the BI design framework proposed by Mason et al.[123,125,129] are presented in Fig. 1 and Table 1.

The framework is based on the model of assistive technology drawn in Fig. 1a. In this model, a person with a functional limitation is depicted on the left. This person desires to perform an activity in his or her environment, which may be to move their body or interact with objects, appliances, physical structures, or other people in the environment. The person's functional limitation results in a gap (shown as the white "ability gap") between the person's abilities and those abilities required by the activity. The resulting inability to perform the desired activity is referred to as a disability. An assistive (or augmentative) technology (AT) can provide the additional functionality that the person requires to bridge the ability gap and perform the desired activity. Like other AT, BI AT provides additional functionality to a target population in order to perform specific (target) activities in certain (target) environments.

Within this context, BI AT can be modeled as a series of components: a BI Transducer and an Assistive Device (as shown in Fig. 1b) or with a Control Interface (as depicted in Fig. 1c). Each of these design components can be represented by a more detailed model. For

[1] To date, the terms Brain–Computer Interface (BCI), Brain–Machine Interface (BMI), Direct Brain Interface (DBI) and Adaptive Brain Interface (ABI) have all been used to describe human interface technology controlled by signals measured directly from the brain. In terms of high-level design, there is essentially no difference between the technologies referred to by these terms. Even though DBI is the most generic term, we have chosen to avoid using any of these terms to reduce interpretation bias in this work. Instead we will us the term Brain Interface as a collective term for this approach to interface technology.

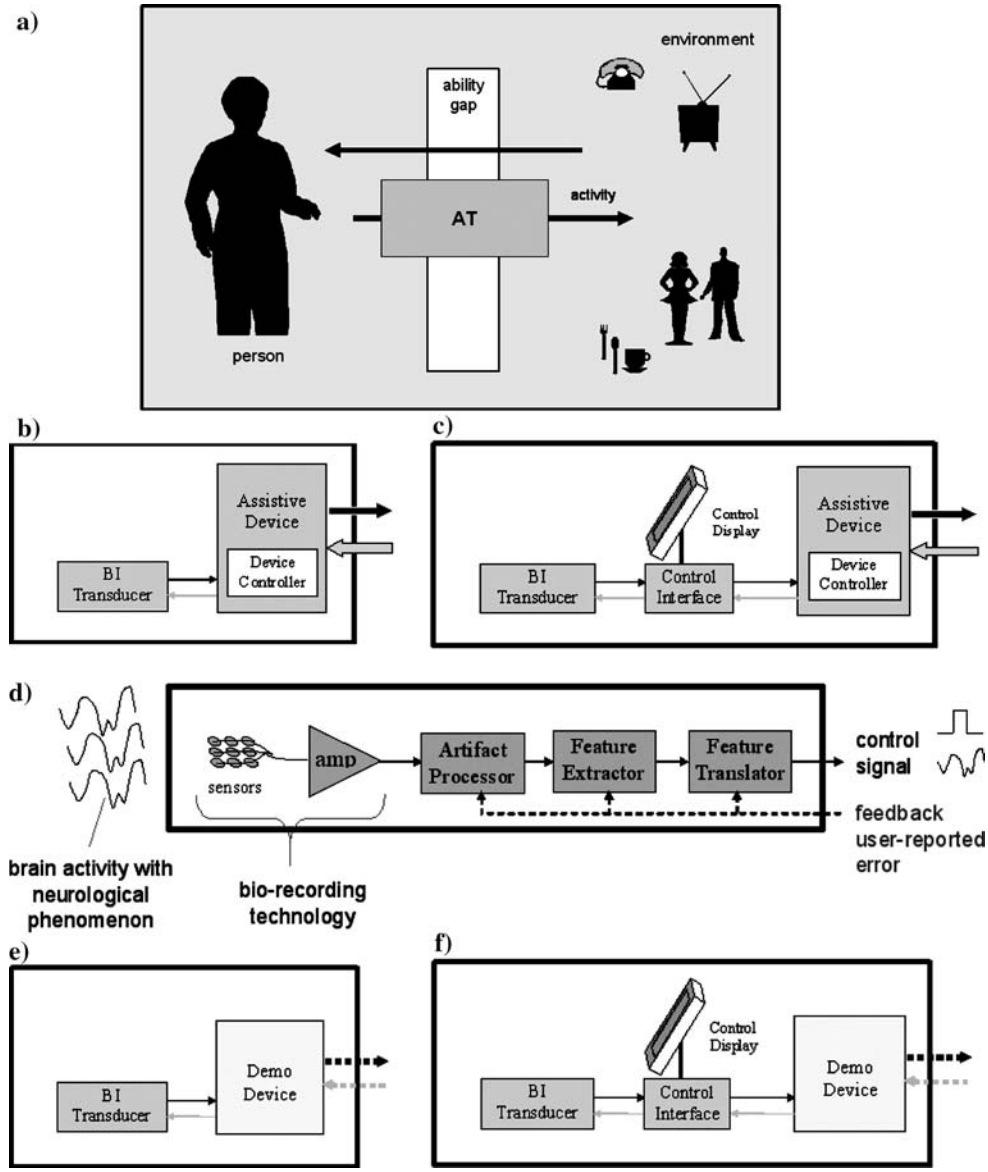

FIGURE 1. Functional models of BI technology design: (a) model of person with a functional limitation able to perform desired activity in the environment with an AT. Icons on the right represent appliances, people or objects in the environment; (b) functional model of 2-component BI AT; (c) functional model of 3-component BI AT, (d) model of an (endogenous) BI Transducer illustrating the series of components used to translate spontaneous brain activity into control signals (note, two other models related to exogenous and modulated-response transducer architectures exist and can be found at Ref. [123]); (e) functional model of 2-component demonstration system, where some form of Demo Device (e.g., a cursor or robotic arm) is used to demonstrate transducer control; (f) functional model of 3-component demonstration system.

example, the BI Transducer can be modeled as the series of components in Fig. 1d that transforms brain activity into a control signal. According to the framework documentation, these models can represent all possible designs. However, readers may be more familiar with other functional terms, such as noise reduction, filtering, preprocessing or spike detection/sorting (which are all forms of feature extraction) and classifier or "decoding method" – or something similar – (which are both terms that describe a specific class of Feature Translator). In this work, we will use the generic component names proposed by the framework to avoid bias toward any design approach.

For many studies, researchers do not employ a full AT model, but use some reduced system in order to demonstrate basic control (as depicted in the Demonstration System models of Fig. 1e and f). Others test only BI Transducer designs.

All of these systems, components and subcomponents can be described in terms of *design attributes*. The taxonomy listed in Table 1, outlines the principal *design attributes* proposed by Mason *et al.*

TABLE 1. BI design taxonomy proposed by Mason et al.[123,125,129]

Design Attribute	Description
Target Application	
Target Population	The target group of people who will use the technology.
Target Activity	The activities that the target population would like to do with the assistive technology.
Target Environment	The location(s) where the assistive technology is designed to be used.
BI AT Design Model	
System Design Model	The general design architecture defining the principle components used in a BI design and their configuration. All but one of the principal design models are presented in Fig. 1. (The one model not shown is the BI Transducer Model which is represents a single BI Transducer)
Principle Design Components	
BI Transducer	The component that translates measured brain activity into basic control signals.
Transducer Design Model	The general architecture used for the transducer design. There are three primary design models: **exogenous** (an external stimulator in used to evoke response from the user), **endogenous** (no stimulator is required as control signals are generate internally) and **modulated response** (a variation on exogenous designs). The reader is directed to [123] for more detail on these models.
Bio-recording Technology	This attribute refers to the class of equipment (sensors, amplifiers, converters and filters) used to measure a person's brain activity in a BI Transducer. Researchers have used EEG, ECoG, custom implanted microelectrode arrays and amplifiers, and functional near infrared. Others have discussed possible fMRI and MEG solutions, but the practicality of these later approaches is suspect.
Neurological Phenomenon	This attribute refers to the phenomenon (or phenomena) used to control a BI Transducer. For example, a P300 response in EEG to an oddball stimulus is a well-studied phenomenon employed in several BI Transducers. Another well-known phenomenon is the increase in neural firing rates measured in microelectrodes as neural activity increases.
Sensor Placement	Sensor Placement identifies the general location of bio-sensors used in a BI Transducer.
Artifact Processor	A component of a BI Transducer that removes artifact from the input signal. Note, many transducer designs do not include artifact processing.
Stimulator (and Stimulus Mechanism)	The Stimulator and its associated Stimulus Mechanism (e.g., strobe lights or flashing areas of a screen) are used to stimulate the user and evoke a response in exogenous or modulated-response transducers. A wide variety of stimuli methods have been used and are directly related to the neurological phenomenon.
Feature Extractor	A component of a BI Transducer that translates the (artifact-free) input brain signal into a value correlated to the neurological phenomenon. The output value is referred to by the Pattern Recognition community as a "feature vector". The function of this component is sometimes referred to as **noise reduction**, **filtering**, **preprocessing** or **spike detection/sorting** depending on the background of the investigator. For example, researchers working with implanted microelectrodes tend to use the terms such as "spike detection" and "spike sorting" instead of Feature Extraction as this tend to be a mores specific description of the type of feature extraction they are performing.
Feature Translator	The component of a BI Transducer that translates the feature vector into a useful control signal. Researchers working with discrete transducer outputs often refer to this component as a Feature Classifier or Classifier as these terms are more specific. For similar reasons, researchers working with implanted microelectrodes use the term "decoding function" (or something similar).
Output	The type and dimensionality of a BI Transducer output. For example, 2-state discrete output, or a one-dimensional, continuous amplitude signal. See BI Transducer – Output in Table 3 for more examples and "Which designs are comparable?" section for definition of terms.
NC Support	This attribute indicates whether the transducer design will support No Control (NC), that is it will produce a stable output when the person using the transducer is not controlling the transducer (i.e., the user is in a "No Control" state). (Note, the opposite of No Control in the taxonomy is Intentional Control – one or more states where the user is intentionally trying to affect the transducer output.) Discrete output (endogenous) transducers that support NC will have an output state/value reserved for No Control. The same is true for exogenous transducers that produce a spatial reference. Continuous output (endogenous) transducers that support NC will ideally hold their output at the last output value produced during Intentional Control.

TABLE 1. Continued.

Design Attribute	Description
Control Interface (CI)	The Component that is added to a transducer that produces a relatively low dimensional output in order to expand the control dimensionality to a level required by an Assistive Device. A good example of a Control Interface is a scanning menu or scanning keyboard where a simple click (a low-dimensional signal) can be translated into a full set of symbols (letters or command).
Interface Paradigm	The type of interface (or interaction style) presented to the user. Examples are menu systems, virtual keyboards, and icon-based point and click interfaces.
Input	The type and dimensionality of the input signals used to operate a Control Interface.
Temporal Control Paradigm	This attribute defines the temporal operation characteristics of the interface. In Ref. [126], we characterized the temporal operation as one of four control paradigms. (1) *synchronized* (periodically available, no NC support); (2) *system-paced* (periodically available, NC support); (3) *constantly-engaged* (continuously available, no NC support); and (4) *self-paced* (continuously available, NC support). This terminology was proposed in Ref. [126] as an alternative to the overloaded adjectives, *asynchronous* and *synchronous*, or *cue-based* and *non-cue-based*.
Translation	The Translation attribute defines the methodology by which the input signals are translated into output signals. For example, a 2-state discrete input may be translated into a full alphanumeric set using an appropriately designed virtual keyboard.
Output	The Output of a Control Interface defines the characteristics of the signals produced by the Control Interface. Generally the output is similar to the type of BI Transducer output although the dimensionality is much higher.
Demo Device (DD)	The Demo Device component represents an infinite range of possible devices used to test the controllability of a BI technology. Devices can provide simple demonstrations of state or level control or they can allow for much more complex control tasks.
Device Type	The Type of Demo Device defines the general class of device being used. For example, a model vehicle, a robotic arm or a monitor with a pointer/cursor. Other examples can be found under Demo Device – Device Type in Table 3.
Type of Control	This attribute defines the general class of actions that a user can perform with the devices: e.g., discrete item selection, moving an object, continuous control of an object.
Dimensionality	The Control Dimensionality defines the range of control (e.g., the number of selectable states, the dimensions of continuous control) the device allows. People sometimes refer to this as the "degrees of freedom" in the device.
Temporal Control Paradigm	Same classes as Temporal Control Paradigm for Control Interfaces (defined above).
Feedback	The Feedback attribute defines the type of feedback from a Demo Device to the user (e.g., visual, aural).
Assistive Device (AD)	The apparatus that interacts directly with objects or people in the environment.
Type	The Type of Assistive Device defines the general class of device being used. For example, a speech synthesizer or FES-based neuroprosthetic. Other examples can be found under Assistive Device – Type in Table 3.
Feedback	The Feedback attribute defines the class of feedback from an Assistive Device to the user (e.g., visual, aural).

METHODS

The designs selected for this survey were chosen from journal and conference papers found in Pubmed, IEEE Xplore or ISI Web of Science databases that met the following criteria: (1) the keywords BI, BCI, BMI, DBI, ABI, or the corresponding descriptions, appeared in their title, abstract or keyword list; and (2) the paper described one or more of the principal design components listed in Table 1 (minimum technology content was a BI Transducer). Papers which presented tutorials, descriptions of new bio-recording technologies (such as new sensor and amplifier designs), overviews of research activities, or neuroanatomy and neurophysiology discussions were not considered. In addition, well-known historical BI-related works such as Vidal[201] and Sutter[190] were also included. Each paper was assigned to a research group using the affiliation of

TABLE 2. Example of *attribute sub-classes* for the *BI-Transducer* – *Bio-recording Technology* design attribute.

Design Attribute	Attribute Sub-Class
BI Transducer	
Bio-recording Technology	***EEG***
	ECoG
	Implanted microelectrodes
	Near Infrared (scalp)

the first author at the time of publication. A research group was defined as the individuals working within a single laboratory or institution or in a group of laboratories or institutions working on a single project. (Refer to Appendix A for a list of research groups.) Papers from a research group that described previously reported designs were not included to avoid counting duplicates. For example, if a research group published two papers that reported different tests with the same technology design, the later paper was not included in our test set.

As we were not evaluating the quality of these designs, that is, how well they worked, but rather collecting design ideas or strategies, we weighted all reported designs equally. Thus designs from journal papers were not stressed more than conference papers in our frequency analysis. Likewise, designs from established laboratories with multiple publications did not carry more weight than those from new researchers with few publications.

A classification template based on the BI design taxonomy listed in Table 1 was constructed for this survey. We extended the taxonomy by adding sub-categories to each *design attribute*. The *attribute sub-classes*, as these sub-categories were named, were initially proposed by our team based on our experience with BI technology and related human–machine interaction research and then refined after an initial pass through the selected papers. To illustrate the concept of *attribute sub-class*, Table 2 depicts the *attribute sub-classes* for ***BI Transducer*** – **Bio-recording Technology** attribute. This example also defines the text style used in this paper to identify attribute names. Specifically, *design attribute* categories such as ***BI Transducer***, are written in a ***bold, italic, sans-serif,*** font, *design attribute* names (like **Bio-recording Technology**) are written in a **serif, bold** type and *attribute sub-classes* (e.g., ***ECoG***) are represented in ***serif, bold-italic*** type. The full classification template with all the *design attributes* and *attribute sub-classes* is listed in the left two columns of Table 3.

Each paper was reviewed by at least two individuals from a team of five reviewers which included the first four authors and a contracted medical student. Reviewers categorized each design by selecting the closest *attribute sub-class* for each *design attribute* defined in the classification template. *Design attributes* that were not reported were recorded as such. For the papers that reported multiple designs or design options, multiple classifications were recorded per paper. The reviewers classified designs based only on what was reported in each paper or referenced works. No personal knowledge of an author's work was used in the classification.

RESULTS AND DISCUSSION

The detailed classification results of the survey are summarized in Table 3. The references listed in the third column represent all the papers that contain designs with the listed *attribute sub-classes*. For instance, all the references listed beside **Target Activity** – ***communication with people (synth. speech, text or drawing)*** are papers with technology designs aimed to help individuals communicate. As such, this table provides a comprehensive historical reference of all BI designs up to January 2006, which can be an extremely valuable resource for technology designers or new researchers entering the field. For example, if one is interested in finding all the BI technology designs that have used movement related potentials in EEG generated by movement imagery, the references to relevant journal and conference papers can be found under ***BI Transducer*** – **Neurological Phenomenon** – ***movement-related potentials from imagined movements***. Alternatively, if one wants an existing virtual keyboard design, they can find the Control Interface designs that emulate a keyboard under ***Control Interface***-**Interface Paradigms**.

In Table 3, papers from the same research group are collected within square brackets separated by a semi-colon. Conference papers are displayed in normal type, e.g., [17] while journal papers are shown in bold type, e.g. [**17**]. The column on the right summarizes the number of research groups, journal papers and conference papers within each *attribute sub-class*. As this work covers technology design and not technology evaluation, there has been no attempt to rate how reliably or accurately the published designs function; that is an issue for manuscript reviewers and readers to interpret once the design details and target applications are understood.

There are many interesting observations or comments which could be made from the results in Table 3. We will first focus our discussion on which BI designs can be compared to each other. Then we will specifically look at what technology designs have been proposed, which target applications have been pursued,

TABLE 3. Results of BI technology design survey. Papers from the same research group are grouped within square brackets, [...], and conference papers are in normal type, e.g., [17], while journal papers are in bold type, e.g., [17]. *Design attribute* names are written in bold type and *attribute sub-classes* will be represented in *bold-italic* type. The column on the right summarizes the number of research groups (g), journal papers (jp) and conference papers (cp) within each *attribute sub-class*.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
Target Application			
Target Population	***Able-bodied individuals***	[104] [133]	2 (**0**, 2)
	Full paralysis (locked-in)	[**117**, **160**] [**15**, **23**, **74**, **75**, **86**, **87**, **106**, **109**, 73] [**14**] [**100**, **156**] [**64**, **65**, **69**, **71**, **149**, **151**; **165**, **173**, 68] [52] [**118**, **176**] [91] [**103**, **167**, 102] [168] [**47**, **207**, **210**, **213**] [**185**] [**26**, **93**, **94**, 25, 95, 96] [**98**] [**48**] [**190**] [**134**] [**21**] [**39**] [**77**] [**81**] [**99**] [**172**, **171**]	23 (**44**, 9)
	Partial paralysis or amputee	[**164**, **162**] [122]	2 (**2**, 1)
	Paralysis (unspecified level)	[3] [12] [**20**, 44, 141] [**30**, **206**] [**146**, **161**] [**92**] [**38**] [**55**, **187**, **186**, **215**] [**97**] [46] [**144**]	11 (**13**, 5)
	Individuals with disabilities (multiple categories or non-specific)	[**61**] [183] [**16**, **22**, **127**, **124**, 9, 24, 121] [**45**, **115**, 104] [**54**, 31] [**105**, **143**, **145**, **163**, **170**, **179**, **181**, 50, 83, 89, 169, 180] [57, 58, 59] [7] [**82**, **194**] [138] [139, 140, 198] [**41**, **157**, **175**, **192**] [**132**, **130**, **131**, **188**, **212**] [**218**] [**112**] [110] [**43**] [**70**] [67, 66] [78, 154] [**113**] [119] [**202**]	23 (**32**, 25)
	Not reported	[**28**, **29**, 42, 174] [**193**] [153] [214] [**152**, 76] [**72**] [**111**, **184**] [**11**, **13**] [**17** , 10, 49] [**18**, **116**, 19, 101] [**33**, **34**, **120**, **205**, **216**, 32, 53, 85, 203, 204] [**63**, **142**, **148**, **150**, **159**, **196**, 88, 114, 182] [60] [**79**, 80] [**5**, **6**, **36**, 4, 35, 37] [**136**, 137] [**1**, **2**, **166**] [**191**] [178] [8] [**27**, **135**] [177] [**197**] [56] [**201**] [**40**] [**84**] [**90**] [**62**] [195, 217] [**155**]	31 (**41**, 29)
Target Activity	***General communication or control (non-specific)***	[**160**, 3] [**23**, 183] [**14**] [**22**, **127**, **124**, 9, 24, 49, 121] [**18**, **20**, **45**, **115**, 44, 101, 141] [**120**, **216**, 31, 53, 85, 203] [**64**, **65**, **69**, **71**, **105**, **142**, **146**, **145**, **163**, **173**, **179**, **181**, 50, 169, 180] [60] [**118**, **176**, 7, 80] [**194**] [**92**] [102] [37, 138] [**136**, 137, 140] [**1**, **2**, **166**] [**157**, **191**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **212**] [**26**, **93**, **94**, **112**, 25, 95, 96] [110] [**98**] [**38**] [177] [**43**] [**187**, **215**, 214] [**134**] [**40**] [**84**] [**39**] [**70**] [217] [**77**, **144**, 78, 154] [**81**] [119] [**172**, **202**]	34 (**61**, 34)
	Communication with people (synth. speech, text or drawing)	[**117**] [**15**, **74**, **75**, **86**, **87**, **106**, **109**, 73] [**149**, **151**, **165**, 114] [52] [57] [91] [**103**, **167**] [**213**] [**185**] [**48**] [**190**] [67, 66] [**113**]	13 (**18**, 7)
	Control of		
	Appliances/devices (e.g., TV, phone, computer, bed)	[**61**] [**11**] [**16**] [19, 104] [**33**, **54**] [**170**, 83, 88, 89] [58, 59] [139, 198] [168] [**41**, **192**] [**218**] [8] [**27**, **135**] [**186**, 56] [**171**]	15 (**13**, 12)
	Objects/avatar in virtual environment (VR, games)	[**13**]	1 (**1**, 0)
	Paralyzed limbs (for body positioning or obj manipulation)	[**16**] [**30**, **100**, **156**, **206**] [**143**, **164**, **162**, **161**, 68] [**82**, **193**] [153] [122] [**55**, **186**, 56] [**97**] [**21**] [46] [**99**]	11 (**16**, 5)
	Vehicle	[133] [**197**]	2 (**1**, 1)
	Personal mobility (e.g., operating a wheelchair)	[**11**, 12]	1 (**1**, 1)
	Not reported	[**28**, **29**, 42, 174] [**152**, 76] [**72**] [**111**, **184**] [**17**, 10] [**116**] [**34**, **205**, 32, 204] [**63**, **148**, **150**, **159**, **196**, 182] [**79**] [**5**, **6**, **36**, 4, 35] [**175**] [178] [**201**] [**90**] [**62**] [195] [**155**]	17 (**24**, 11)
Target Environment	***General living environments/ home***	[**160**] [**87**] [49] [**54**] [110]	5 (**3**, 2)
	Other	[133]	1 (**0**, 1)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
	Not reported	[**61**, 3] [**117**] [**15**, **23**, **74**, **75**, **86**, **106**, **109**, **111**, **184**, 73, 183] [**11**, **14**, **13**, 12] [**16**, **17**, **22**, **127**, **124**, 10, 9, 24, 121] [**18**, **20**, **45**, **115**, **116**, 19, 44, 101, 104, 141] [**33**, **34**, **120**, **205**, **216**, 31, 32, 53, 85, 203, 204] [**28**, **29**, **30**, **100**, **156**, **206**, 42, 174] [**63**, **64**, **65**, **69**, **71**, **105**, **143**, **142**, **146**, **145**, **148**, **149**, **150**, **151**, **159**, **164**, **162**, **163**, **165**, **161**, **170**, **173**, **179**, **181**, **196**, 50, 68, 83, 88, 89, 114, 169, 180, 182] [52] [57, 58, 59, 60] [**79**, **118**, **176**, 7, 80] [**82**, **193**, **194**] [91] [**92**] [**103**, **167**, 102] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 139, 140, 198] [153] [**1**, **2**, **166**] [168] [**41**, **157**, **175**, **191**, **192**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**185**, **218**] [**26**, **93**, **94**, **112**, 25, 95, 96] [178] [8] [**98**] [**27**, **135**] [**38**] [177] [122] [**197**] [**43**, **48**] [**55**, **187**, **186**, **215**, 56, 214] [**201**] [**190**] [**97**] [**134**] [**40**] [**84**] [**90**] [**21**] [**152**, 76] [**39**] [**70**] [**72**] [46] [**62**] [67, 66, 195, 217] [**77**, **144**, **155**, 78, 154] [**81**, **113**] [**99**] [119] [**172**, **171**, **202**]	55 (**129**, 67)
System Design Model			
System Design Model	***Full AT***		
	2-component (T-AD)	[**54**] [**143**, **162**, **161**, 68] [67]	3 (**4**, 2)
	3-component (T-CI-AD)	[**15**, **74**, **86**, **106**] [**33**] [**149**, **179**] [91] [**98**] [**48**] [**190**]	7 (**10**, 1)
	Demonstration System ***2-component (T-DD)***	[**117**] [**75**, **87**, **109**, 73, 183] [**11**, **14**, **13**, 12] [**16**, **127**, 24, 121] [31, 203] [**28**, **29**, **30**, **206**] [**69**, **71**, **105**, **142**, **146**, **148**, **150**, **164**, **163**, **165**, **170**, 114, 180] [52] [59] [**193**, **194**] [**103**, **167**, 102] [**136**, 139] [**1**, **2**] [**132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**185**] [**94**, **112**, 95, 96] [110] [**27**, **135**, 133] [**197**] [**43**] [**187**, **215**, 214] [**201**] [**152**, 76] [**62**] [66, 195] [**113**, **144**]	26 (**53**, 21)
	3-component (T-CI-DD)	–	0 (**0**, 0)
	Transducer (T)	[**61**, **160**, 3] [**23**, **111**, **184**] [**17**, **22**, **124**, 10, 9, 49] [**18**, **20**, **45**, **115**, **116**, 19, 44, 101, 104, 141] [**34**, **120**, **205**, **216**, 32, 53, 85, 204] [**100**, **156**, 42, 174] [**63**, **64**, **65**, **145**, **151**, **159**, **173**, **181**, **196**, 50, 83, 88, 89, 169, 182] [57, 58, 60] [**79**, **118**, **176**, 7, 80] [**82**] [**92**] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 140, 198] [153] [**166**] [168] [**41**, **157**, **175**, **191**, **192**] [**47**] [**218**] [**26**, **93**, 25] [178] [8] [**38**] [177] [122] [**55**, **186**, 56] [**97**] [**134**] [**40**] [**84**] [**90**] [**21**] [**39**] [**70**] [**72**] [46] [**62**] [217] [**77**, **155**, 78, 154] [**81**] [**99**] [119] [**172**, **171**, **202**]	43 (**67**, 46)
Principle Design Components			
BI Transducer			
Transducer Design Model	***Endogenous***	[**61**, **160**, 3] [**117**] [**15**, **23**, **74**, **75**, **86**, **87**, **106**, **109**, **111**, **184**, 183] [**16**, **17**, **22**, **127**, **124**, 10, 9, 24, 49, 121] [**18**, **20**, **45**, **115**, **116**, 19, 44, 101, 104, 141] [**34**, **120**, **205**, 85] [**28**, **29**, **30**, **100**, **156**, **206**, 42, 174] [**63**, **64**, **65**, **69**, **71**, **105**, **143**, **146**, **145**, **148**, **149**, **150**, **151**, **159**, **164**, **162**, **163**, **165**, **161**, **170**, **173**, **179**, **181**, **196**, 50, 68, 83, 88, 89, 114, 169, 180, 182] [57, 58, 59, 60] [**79**, **118**, **176**, 7, 80] [**82**, **193**, **194**] [**92**] [**103**, **167**, 102] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 139, 140, 198] [153] [**166**] [**41**, **157**, **175**, **191**, **192**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**218**] [**26**, **93**, 25] [110] [178] [8] [**98**] [**38**] [177] [122] [**197**] [**55**, **187**, **186**, **215**, 56, 214] [**97**] [**134**] [**40**] [**21**] [**152**, 76] [**39**] [**70**] [**72**] [46] [**62**] [217] [**77**, **144**, **155**, 78, 154] [**81**] [**99**] [119] [**172**, **171**, **202**, **202**]	46 (**112**, 54)
	Exogenous	[**23**] [**11**, **14**, **13**, 12] [**33**, **54**, **216**, 31, 32, 53, 203, 204] [**142**] [52] [91] [**1**, **2**] [168] [**185**] [**94**, **112**, 95, 96] [**43**, **48**] [**201**] [**190**] [**84**] [**90**] [**62**] [67, 66, 195] [**113**]	18 (**21**, 14)
	Modulated response	[73] [**27**, **135**, 133]	2 (**2**, 2)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
Neurological Phenomenon	***Changes in cell firing rate***		
	Related to attempted movement	[**28**, **29**, **30**, **100**, **156**, **206**, 42, 174] [**82**, **193**, **194**] [153] [**98**] [**55**, **187**, **186**, **215**, 56, 214] [**97**] [**152**, 76] [**72**] [**99**]	9 (**18**, 6)
	Related to imagined movement	–	0 (**0**, 0)
	Related to cognitive task	[**144**]	1 (**1**, 0)
	In response to stimuli	–	0 (**0**, 0)
	Mu, alpha, beta or other rhythm power	[**117**] [**109**, **111**] [10] [**18**, **115**, **116**] [**34**] [**105**, **161**, 50, 89, 114] [**103**, **167**, 102] [**166**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [110] [8] [**197**] [**134**] [119]	14 (**23**, 8)
	ERD or ERS	[**45**, 104, 141] [**205**, 85] [**69**, **143**, **146**, **145**, **148**, **150**, **164**, **162**; **163**, **165**, **170**, **173**, 68, 83, 88, 169, 180] [80] [8] [**172**, **171**, **202**]	6 (**17**, 10)
	Movement-related potentials		
	From attempted movement	[**17**, **22**, **127**, 49, 121] [**20**, **45**, 19, 44, 101, 104, 141] [**120**, **205**] [**63**, **64**, **65**, **159**, 182] [**79**, **118**, **176**, 7, 80] [**218**] [**26**, **93**, 25] [**40**] [217]	9 (**18**, 12)
	From imagined movements	[**184**] [**16**, **124**, 9, 24] [**71**, **149**, **179**, **181**, **196**] [59, 60] [**5**, **6**, **36**, 4, 35, 37] [**136**] [**191**] [178] [**38**] [122] [**21**] [**39**] [46] [**62**] [**81**]	15 (**18**, 10)
	P300 (or N100) response	[**23**] [**11**, **14**, **13**, 12] [**216**, 53] [52] [91] [**1**, **2**] [168] [**185**] [**43**, **48**] [**84**] [**90**] [**62**] [67, 195]	13 (**13**, 7)
	Slow-cortical potentials (SCPs)	[**15**, **23**, **74**, **75**, **86**, **87**, **106**, 183] [**134**]	2 (**8**, 1)
	Response to basic cognitive tasks	[**160**, 3] [**92**] [138] [137, 139, 140, 198] [**191**, **192**] [**70**] [**77**, 78, 154]	7 (**6**, 8)
	SSVEP response to visual stimulus	[**33**, **54**, 31, 32, 203, 204] [**142**] [**94**, **112**, 95, 96] [**190**] [**113**]	5 (**7**, 6)
	VEP response to visual stimulus	[**201**] [66]	2 (**1**, 1)
	Audio/aural evoked potentials (AEP)	[73]	1 (**0**, 1)
	Conscious modulation of brain response to stimuli	[**27**, **135**, 133]	1 (**2**, 1)
	Other phenomena	[10] [**6**] [177]	3 (**1**, 2)
	Multiple phenomena	[**61**] [**151**] [57, 58] [**41**, **157**, **175**] [**155**]	5 (**6**, 2)
Bio-recording Technology	***EEG***	[**61**, **160**, 3] [**15**, **23**, **74**, **75**, **86**, **87**, **106**, **109**, **111**, **184**, 73, 183] [**11**, **14**, **13**, 12] [**16**, **17**, **22**, **127**, **124**, 10, 9, 24, 49, 121] [**18**, **20**, **45**, **115**, **116**, 19, 44, 101, 104, 141] [**33**, **34**, **54**, **120**, **205**, **216**, 31, 32, 53, 85, 203, 204] [**69**, **71**, **105**, **143**, **142**, **146**, **145**, **148**, **149**, **150**, **151**, **159**, **164**, **162**, **163**, **165**, **161**, **170**, **173**, **179**, **181**, **196**, 50, 68, 83, 88, 89, 114, 169, 180, 182] [52] [57, 58, 59, 60] [91] [**92**] [**103**, **167**, 102] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 139, 140, 198] [**1**, **2**, **166**] [168] [**41**, **157**, **175**, **191**, **192**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**185**, **218**] [**26**, **93**, **94**, **112**, 25, 95, 96] [110] [178] [8] [**27**, **135**, 133] [**38**] [177] [122] [**197**] [**43**, **48**] [**201**] [**190**] [**134**] [**84**] [**90**] [**21**] [**39**] [**70**] [46] [**62**] [67, 66, 195, 217] [**77**, **155**, 78, 154] [**81**, **113**] [119] [**172**, **171**, **202**, **202**]	44 (**106**, 62)
	ECoG	[**117**] [**63**, **64**, **65**] [**79**, **118**, **17 6**, 7, 80] [**190**]	4 (**8**, 2)
	Implanted microelectrodes	[**28**, **29**, **30**, **100**, **156**, **206**, 42, 174] [**82**, **193**, **194**] [153] [**98**] [**55**, **187**, **186**, **215**, 56, 214] [**97**] [**152**, 76] [**72**] [**99**, **144**]	9 (**19**, 6)
	Near Infrared (scalp)	[**40**]	1 (**1**, 0)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
Sensor Placement	***In/over motor cortex***	[**74**, **86**, **87**, **106**, **111**, 183] [**16**, **17**, **127**, 9, 49] [101] [53, 85] [**100**] [**71**, **105**, **146**, **148**, **149**, **150**, **164**, **162**, **163**, **165**, **170**, 68, 88, 89, 180, 182] [52] [60] [**157**, **175**] [**188**] [**26**, **93**, 25] [**38**] [**152**, 76] [**39**] [**72**] [217] [**99**]	17 (**30**, 16)
	In/over somatosensory cortex	[**22**, 24] [**116**] [**205**] [**30**, **206**, 42] [**63**, **143**, **161**, **179**, 114] [**79**, **118**, **176**, 7, 80] [**82**, **193**, **194**] [153] [**130**, **131**, **213**, **212**] [**98**] [**55**, **187**, **186**, **215**, 56, 214] [**134**] [**40**] [**21**] [**62**] [67] [**81**]	17 (**29**, 9)
	In/over occipital cortex	[**33**, **54**, 31, 32] [**142**] [**94**, **112**, 95] [**27**, **135**, 133] [**190**] [**113**]	6 (**9**, 4)
	In/over parietal cortex	[**43**, **48**] [**84**] [**144**]	3 (**4**, 0)
	In/over temporal cortex	–	0 (**0**, 0)
	In/over multiple cortical areas	[**61**, **160**, 3] [**117**] [**15**, **23**, **109**, **184**, 73] [**11**, **14**, **13**, 12] [**124**, 10, 121] [**18**, **20**, **45**, **115**, 19, 44, 104, 141] [**34**, **120**, **216**, 203, 204] [**28**, 174] [**64**, **65**, **69**, **145**, **151**, **159**, **173**, **181**, **196**, 50, 83, 169] [57, 58, 59] [91] [**92**] [**103**, **167**, 102] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 139, 140] [**1**, **2**, **166**] [168] [**41**, **191**, **192**] [**47**, **132**, **207**, **210**] [**185**, **218**] [96] [110] [178] [8] [177] [122] [**197**] [**201**] [**190**] [**97**] [**90**] [**70**] [46] [66, 195] [**77**, **144**, **155**, 78, 154] [119] [**172**, **171**, **202**]	37 (**59**, 40)
	Not reported	[**75**] [198]	2 (**1**, 1)
Artifact Processing	***OA and EMG removed***	[**13**, 12] [**163**] [**93**] [**81**]	4 (**4**, 1)
	OA removed	[**74**, **106**] [**11**, **14**] [122] [46] [67, 195] [119]	6 (**4**, 5)
	None	[**61**, **160**, 3] [**117**] [**15**, **23**, **75**, **86**, **87**, **109**, **111**, **184**, 73, 183] [**16**,**17**,**22**, **127**,**124**,10,9; 24,49,121] [**18**, **20**, **45**, **115**, **116**, 19, 44, 101, 104, 141] [**33**, **34**, **54**, **120**, **205**, **216**, 31, 32, 53, 85, 203, 204] [**28**, **29**, **30**, **100**, **156**, **206**, 42, 174] [**63**,**64**,**65**,**69**,**71**,**105**,**143**,**142**,**146**,**145**; **148**,**149**,**150**,**151**,**159**, **164**,**162**,**165**,**161**,**170**,**173**,**179**,**181**,**196**,50,68,83,88,89,114, 169,180,182] [52] [57, 58, 59, 60] [**79**, **118**, **176**, 7, 80] [**82**, **193**, **194**] [91] [**92**] [**103**, **167**, 102] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 139, 140, 198] [153] [**1**, **2**, **166**] [168] [**41**, **157**, **175**, **191**, **192**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**185**, **218**] [**26**, **94**, **112**, 25, 95, 96] [110] [178] [8] [**98**] [**27**, **135**, 133] [**38**] [177] [**197**] [**43**, **48**] [**55**, **187**, **186**, **215**, 56, 214] [**201**] [**190**] [**97**] [**134**] [**40**] [**84**] [**90**] [**21**] [**152**, 76] [**39**] [**70**] [**72**] [**62**, **62**] [66, 217] [**77**, **144**, **155**, 78, 154] [**113**] [**99**] [**172**, **171**, **202**]	52 (**125**, 64)
Stimulus Mechanism	***Flashing area of a screen***	[**23**] [**11**, **14**, **13**, 12] [**33**, **216**, 31, 32, 53, 204] [52] [**1**, **2**] [168] [**185**] [**94**, 95, 96] [**43**, **48**] [**201**] [**190**] [**90**] [**62**] [67, 66, 195]	14 (**16**, 12)
	Strobe lights	[**54**, 203] [**142**] [91] [**27**, **135**, 133] [177] [**113**]	6 (**5**, 4)
	Other mechanism	[**84**]	1 (**1**, 0)
	Tones	[177]	1 (**0**, 1)
Feature Extraction	***No feature extraction (input = feature)***	[3] [**74**] [**71**] [**193**] [8] [**72**] [66]	7 (**4**, 3)
	Single observation methods:		
	Calculation of single cell neural firing rate	[**28**, **29**, **156**, **206**, 174] [**194**] [**98**] [**55**, **187**, **186**, **215**, 56, 214] [**97**] [**152**, 76] [**99**]	7 (**13**, 4)
	Power/signal amplitude in single frequency band	[**15**, **74**, **75**, **86**, **87**, **106**, 183] [10] [19, 44, 101, 104, 141] [**33**, **34**, 31, 32, 203] [**164**, **161**, **179**, 50, 83, 88, 89, 169] [**176**] [102] [**166**] [**47**, **132**, **130**, **131**, **188**, **213**, **212**] [**93**, **94**, 95, 96] [**27**, **135**] [**134**] [**40**] [**84**] [**21**] [46]	16 (**28**, 19)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
	Coherence or phase calculation	[**70**]	1 (**1**, 0)
	Signal amplitude differences	[**120**]	1 (**1**, 0)
	Matched filter (correlation with template)	[**13**, 12] [**64**] [**79**, **118**, 7, 80] [**166**]	4 (**5**, 3)
	Power/signal amplitude in multiple frequency bands	[**117**] [**109**] [**45**] [**54**, **120**, 85] [**105**, **143**, **142**, **145**, **151**, **163**, **165**, **170**, 114, 169] [60] [**92**] [**167**] [**6**, 4, 35, 37] [198] [**207**, **210**] [**218**] [**112**] [110] [178] [133] [177] [122] [**134**] [**155**, 154] [**202**]	21 (**23**, 14)
	AR/AAR modeling	[**61**, 3] [**111**, **184**] [**45**, 141] [**65**, **146**, **148**, **149**, **159**, **162**, **165**, **181**, 68, 180, 182] [80] [**92**] [**103**] [198] [**157**, **175**, **191**, **192**] [**210**] [**26**, **93**, 25] [**77**, 78]	12 (**22**, 9)
	Independent comp. analysis (ICA)	[73] [**13**, 12] [**216**, 53, 204]	3 (**2**, 4)
	Kalman filtering	[**13**, 12] [**65**]	2 (**2**, 1)
	KL Transform (PCA)	[3] [**30**] [**82**] [**166**] [76] [195]	6 (**3**, 3)
	Wavelet transform	[**23**, **74**] [**116**] [**63**, **64**] [52] [80] [91] [198] [**84**] [**62**] [**144**]	10 (**8**, 4)
	Custom/other transform	[**160**, 3] [**74**] [**16**, **17**, **22**, **127**, **124**, 10, 9, 24, 49, 121] [**18**, **20**, **115**, 141, 141] [**205**] [**100**, 42] [**69**, **148**, **150**, **173**, **196**] [57, 58, 59, 60] [80] [**5**, **36**, 138] [**136**, 137, 139, 140] [153] [**166**] [**41**] [**38**] [**197**] [**201**] [**84**] [**21**] [**39**] [67, 217] [**81**] [119] [**172**, **171**]	24 (**31**, 22)
	Multi-observation methods:		
	Correlation of temporal average of stimulus locked response with template	[**43**, **48**] [**190**] [**90**] [**113**]	4 (**5**, 0)
	Size of temporal average of stimulus locked response	[**11**, **14**] [**1**, **2**] [168] [**185**] [**48**]	5 (**6**, 1)
Feature Translation	*Linear classifiers:*		
	Thresholding	[**74**, **75**, **86**, **87**, **106**] [**11**, **13**, 12] [**17**] [101] [**33**, **54**, 31, 32, 53, 203] [**63**, **64**, **65**, **161**, **196**] [**79**, **118**, **176**, 7, 80] [91] [102] [153] [**1**, **2**, **166**] [168] [**130**, **131**, **212**] [**185**] [**94**] [**27**, **135**, 133] [**43**, **48**] [**190**] [**40**] [**84**] [**113**] [**172**, **171**, **202**]	22 (**37**, 13)
	Baysean	[**116**] [**157**, **175**, **192**] [**201**] [76] [**72**] [**144**]	6 (**7**, 1)
	LDA	[**61**] [**23**, **74**] [**18**, **20**, **45**, **115**, 19, 44, 104, 141] [**120**, 85] [**69**, **143**, **142**, **146**, **149**, **164**, **162**, **165**, **179**, **181**, 68, 114, 180, 182] [52] [60] [80] [**5**, **36**] [**47**] [**26**, **93**, **112**, 25, 95, 96] [**134**] [**21**] [**39**] [67] [**81**]	16 (**28**, 16)
	Other	[**74**] [**14**] [**34**, **216**] [**173**] [**6**, **36**, 4, 35] [**136**, 137] [**41**, **191**] [**186**]	8 (**11**, 3)
	Nonlinear classifiers		
	k-Nearest Neighbours (LVQ)	[**16**, **22**, **127**, **124**, 9, 24, 121] [19] [**145**, **163**, **165**, **170**, **181**, 50, 88, 89, 169] [**82**] [**36**, 37] [178]	6 (**11**, 10)
	ART, ARTMap, fuzzy ART	[**155**]	1 (**1**, 0)
	Hidden Markov Model	[42] [**148**, **150**, **151**] [37]	3 (**3**, 2)
	Neural Network (NN)	[**61**, 3] [**205**, 204] [**30**, **206**] [**71**, **159**] [52] [58] [**194**] [**103**, **167**] [37, 138] [**136**, 137, 139, 140, 198] [8] [**38**] [177] [122] [**21**] [46] [**77**, 78, 154]	17 (**13**, 16)
	Support Vector Machines	[**61**, **160**] [**111**, **184**, 73, 183] [19] [**181**] [57, 59, 60] [**218**] [**197**] [**90**] [**152**] [**70**] [**62**] [66, 195, 217]	12 (**11**, 9)
	Other nonlinear classifier	[83] [**92**] [**41**]	3 (**2**, 1)
	Linear continuous transformation	[**117**] [**15**, **109**] [10] [**28**, **29**, **100**, **156**, 174] [**105**] [**132**, **188**, **207**, **210**, **213**] [110] [**197**] [**55**, **187**, **215**, 56, 214] [**97**] [**72**] [**99**] [119]	13 (**20**, 6)
	Nonlinear continuous transformation	[**98**] [56] [**72**]	3 (**2**, 1)
	Other	[**193**]	1 (**1**, 0)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
Output	***Discrete (all IC states)***		
	2 -state	[**160**, 3] [**23**, **111**, **184**, 73] [**18**, **20**, **45**, **115**, **116**, 44, 101, 104, 141] [**205**, 85] [**69**, **71**, **143**, **145**, **162**, **163**, **165**, **170**, **173**, 50, 68, 88, 89, 114, 169, 180, 182] [59, 60] [**92**] [**5**, **6**, **36**, 4, 35, 37] [**166**] [**41**, **192**] [**185**, **218**] [**26**, **93**, **112**, 25] [178] [8] [**38**] [177] [**186**] [**134**] [**40**] [**21**] [**152**, 76] [**39**] [46] [**62**] [217] [**81**] [**172**, **171**, **202**]	27 (**43**, 27)
	3-state	[44] [**151**, **159**, 169] [198] [**47**] [122] [**155**]	6 (**4**, 4)
	4-state	[**34**, **120**, 203] [**181**, 83] [**197**] [**186**] [**144**]	5 (**6**, 2)
	5-state	[**61**] [**77**, **144**, 78, 154]	2 (**3**, 2)
	6-state	[**144**]	1 (**1**, 0)
	8-state	[**193**] [**186**] [**72**] [**144**]	4 (**4**, 0)
	Discrete (with 1 unknown state)		
	3-state	[57, 58] [**136**, 137] [**157**, **175**, **191**] [**70**]	4 (**5**, 3)
	4-state	[138] [**136**, 139, 140]	2 (**1**, 3)
	Discrete (with 1 No Control state)		
	2-state	[**16**, **17**, **22**, **127**, **124**, 9, 24, 49, 121] [19] [**30**, 42] [**63**, **64**, **65**, **164**, **161**, **179**, **196**] [**79**, **118**, **176**, 7, 80] [**82**] [153]	7 (**17**, 9)
	3-state	[**27**]	1 (**1**, 0)
	Discrete (1 state = unknown and 1 state = No Control)		
	Continuous – fixed reference		
	1-D (like a stereo volume control)	[10] [**146**, **148**, **149**, **150**] [**197**]	3 (**5**, 1)
	2-D (like a joystick)	[**55**, **187**, **186**, **215**, 56, 214]	1 (**4**, 2)
	3-D (like a 3-D joystick)	–	0 (**0**, 0)
	Relative continuous - no reference		
	1-D (like the wheel on a wheel mouse)	[**117**] [**15**, **74**, **75**, **86**, **87**, **106**, **109**, 183] [**105**] [**103**, **167**, 102] [**132**, **130**, **131**, **188**, **210**, **212**] [110] [**98**] [**135**, 133] [**97**] [119]	10 (**20**, 5)
	2-D (like a mouse position control)	[**29**, **156**, 174] [**103**] [**207**, **213**] [**72**] [**99**]	5 (**7**, 1)
	3-D (like a 3-D mouse position control)	[**100**, **206**] [**194**]	2 (**3**, 0)
	2-D spatial reference – point or region	[**13**, 12] [**84**]	2 (**2**, 1)
	1 region	[**13**, 12] [**84**]	2 (**2**, 1)
	2 regions	[**185**] [**94**, **112**, 95, 96]	2 (**3**, 2)
	4 regions	[31] [**142**] [**201**]	3 (**2**, 1)
	5 regions	[**11**, **14**] [91]	2 (**2**, 1)
	10 regions	[204]	1 (**0**, 1)
	13 regions	[**33**]	1 (**1**, 0)
	16 regions	[**1**]	1 (**1**, 0)
	24 regions	[32]	1 (**0**, 1)
	26 regions	[66]	1 (**0**, 1)
	36 regions	[**23**] [**216**, 53] [52] [168] [**43**, **48**] [**90**] [**62**] [67, 195]	8 (**6**, 5)
	48 regions	[**54**]	1 (**1**, 0)
	64 regions	[**1**, **2**] [**190**] [**113**]	3 (**4**, 0)
	144 regions	[**1**]	1 (**1**, 0)
	Multiple – discrete outputs	–	0 (**0**, 0)
	Multiple – continuous outputs	[**28**]	1 (**1**, 0)
	Multiple – hybrid outputs	–	0 (**0**, 0)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
NC Support	***NC supported***	[**16**, **17**, **22**, **124**, 9, 24, 49, 121] [19] [**30**, 42] [**63**, **64**, **65**, **161**, **179**, **196**] [**79**, **118**, **176**, 7, 80] [**82**] [**27**]	7 (**16**, 8)
	NC not supported	[**2**]	1 (**1**, 0)
	Not reported	[**61**, **160**, 3] [**117**] [**15**, **23**, **74**, **75**, **86**, **87**, **106**, **109**, **111**, **184**, 73, 183] [**11**, **14**, **13**, 12] [**127**, 10] [**18**, **20**, **45**, **115**, **116**, 44, 101, 104, 141] [**33**, **34**, **54**, **120**, **205**, **216**, 31, 32, 53, 85, 203, 204] [**28**, **29**, **100**, **156**, **206**, 174] [**69**, **71**, **105**, **143**, **142**, **146**, **145**, **148**, **149**, **150**, **151**, **159**, **164**, **162**, **163**, **165**, **170**, **173**, **181**, 50, 68, 83, 88, 89, 114, 169, 180, 182] [52] [57, 58, 59, 60] [**193**, **194**] [91] [**92**] [**103**, **167**, 102] [**5**, **6**, **36**, 4, 35, 37, 138] [**136**, 137, 139, 140, 198] [153] [**1**, **166**] [168] [**41**, **157**, **175**, **191**, **192**] [**47**, **132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**185**, **218**] [**26**, **93**, **112**, 25, 95, 96] [110] [178] [8] [**98**] [**135**, 133] [**38**] [177] [122] [**197**] [**43**, **48**] [**55**, **187**, **186**, **215**, 56, 214] [**201**] [**190**] [**97**] [**134**] [**40**] [**84**] [**90**] [**21**] [**152**, 76] [**39**] [**70**] [**72**] [46] [**62**] [67, 66, 195, 217] [**77**, **144**, **155**, 78, 154] [**81**, **113**] [**99**] [119] [**172**, **171**, **202**]	55 (**114**, 62)
Control Interface			
Interface Paradigm	***Virtual keyboard***		
	Single direct selection	–	0 (**0**, 0)
	Single indirect (pointer-based) selection	[**98**]	1 (**1**, 0)
	Multiple direct selections	[**149**, **179**]	1 (**2**, 0)
	Multiple indirect (pointer-based) selections	[**15**, **74**, **106**]	1 (**3**, 0)
	Menu system		
	Single direct selection	[**33**] [91] [**48**] [**190**] [67]	5 (**3**, 2)
	Single indirect (pointer-based) selection	[**98**]	1 (**1**, 0)
	Multiple direct selections	–	0 (**0**, 0)
	Multiple indirect (pointer-based) selections	[**86**]	1 (**1**, 0)
	Icon based point and click	–	0 (**0**, 0)
CI Input	***Discrete*** (**1 NC state**) 2 -state	[**179**]	1 (**1**, 0)
	1-D continuous – fixed reference	[**149**]	1 (**1**, 0)
	1-D relative continuous – no reference	[**15**, **74**, **86**, **106**] [**98**]	2 (**5**, 0)
	2D spatial reference – point or region		
	5 regions	[91]	1 (**0**, 1)
	13 regions	[**33**]	1 (**1**, 0)
	36 regions	[**48**] [67]	2 (**1**, 1)
	64 regions	[**190**]	1 (**1**, 0)
Temporal Control Paradigm	***Synchronized***	[**15**, **74**, **86**, **106**] [**33**] [**149**, **179**] [91] [**48**] [**190**] [67]	7 (**9**, 2)
	Constantly engaged	–	0 (**0**, 0)
	System-paced	–	0 (**0**, 0)
	Self-paced	[**98**]	1 (**1**, 0)
CI Output	***Discrete N-state input (all IC states)***	[**15**, **74**, **86**, **106**] [**33**] [**149**, **179**] [91] [**98**] [**48**] [**190**] [67]	8 (**10**, 2)
	Continuous	–	0 (**0**, 0)
	Spatial reference	–	0 (**0**, 0)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
On Mechanism	***Automated***	[**86**] [**33**]	2 (**2**, 0)
	Manual (assumed if not reported)	[**15**, **74**, **106**] [10] [**149**, **179**] [91] [**5**] [**98**] [**48**] [**190**] [67]	9 (**9**, 3)
Demo Device **Type**	***Computer monitor with:***		
	Bar or level indicator	[**71**, **146**, **148**, **150**] [110] [**135**]	3 (**5**, 1)
	Discrete indicator	[73] [**163**, **165**, **170**, 180] [95, 96] [**144**]	4 (**4**, 4)
	Cursor + discrete functions (like a mouse)	[**113**]	1 (**1**, 0)
	Cursor	[**117**] [**75**, **87**, **109**, 183] [**28**, **29**, **206**] [**105**] [**193**, **194**] [**103**, **167**, 102] [**132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**187**, **186**, **215**, 214]	8 (**23**, 3)
	Menu system	[52] [**1**, **2**] [**185**] [**43**] [62] [66]	6 (**4**, 3)
	Object(s) in virtual world (video game or VR)	[**11**, **14**, **13**, 12] [**16**, **127**, 24, 121] [31] [**69**, **142**, 114] [59] [**112**] [**201**]	7 (**9**, 6)
	Other virtual device used to demonstrate direct brain control	[**105**, 182]	1 (**1**, 1)
	Model vehicle	[**136**, 139]	1 (**1**, 1)
	Robotic arm / hand	[**206**] [**194**]	2 (**2**, 0)
	Vehicle simulator	[**27**, **135**, 133]	1 (**2**, 1)
	Other device used to demonstrate direct brain control	[203] [**30**] [**152**, 76]	3 (**2**, 2)
Type of Control	***Object selection – direct item/(parameter) value/action selection***	[73] [**11**, **14**, **13**, 12] [**16**, **127**, 24, 121] [203] [**30**] [**69**, **105**, **142**, **163**, **165**, **170**, 114, 180, 182] [52] [**136**] [**1**, **2**] [**185**] [**112**, 95, 96] [**27**] [**43**] [**152**, 76] [62] [66] [**144**]	17 (**21**, 14)
	Object selection – indirect (pointer based) item/(parameter) value/action selection	[**113**]	1 (**1**, 0)
	Continuous value adjustment	[**28**] [**71**, **146**, **148**, **150**] [110]	3 (**5**, 1)
	Object positioning		
	Move object from fixed starting point(s) to 1 target per trial	[**117**] [**75**, **109**, 183] [31] [**105**] [**103**, **167**, 102] [**132**, **131**, **188**, **207**, **210**, **213**, **212**]	6 (**13**, 3)
	Move object from fixed starting point(s) to 1 of N possible targets	[**87**] [**193**, **194**] [**130**] [133]	4 (**4**, 1)
	Continuous positioning (path not important)	[**28**, **29**, **206**] [59] [139] [**135**] [**186**, **215**, 214] [**201**]	6 (**7**, 3)
	Continuous path following/ navigation /drawing (where path is important)	[**187**]	1 (**1**, 0)
Dimensionality	***1 of 1 item (or value) selected - hit or time out***	[**13**, 12] [**16**, **127**, 24, 121] [**30**]	3 (**4**, 3)
	1 of 2 items selected	[73] [**69**, **105**, **163**, **165**, **170**, 114, 180, 182] [**112**, 95, 96] [**27**] [**152**, 76]	5 (**8**, 7)
	1 of 3–10 items selected	[**11**, **14**] [**142**] [52] [**136**] [**144**]	5 (**5**, 1)
	1 of more than 10 items selected	[203] [**1**, **2**] [**185**] [**43**] [62] [66] [**113**]	7 (**5**, 3)
	In 1-D (object positioning or continuous value adjustment)	[**117**] [**75**, **87**, **109**, 183] [**28**] [**71**, **105**, **146**, **148**, **150**] [**103**, **167**, 102] [**132**, **130**, **131**, **188**, **210**, **212**] [110] [**135**, 133]	8 (**19**, 4)

TABLE 3. Continued.

Design Attribute	Attribute Sub-Class	Papers with Attribute Sub-Class	Counts g (jp,cp)
	In 2-D	[31] [**28**, **29**] [59] [**103**] [139] [**207**, **213**] [**187**, **186**, **215**, 214] [**201**]	8 (**9**, 4)
	In 3-D	[**206**] [**193**, **194**]	2 (**3**, 0)
Temporal Control Paradigm	***Synchronized***	[**117**] [**75**, **87**, **109**, 73, 183] [**11**, **14**, **13**, 12] [31] [**69**, **105**, **105**, **142**, **163**; **165**, **170**, 114, 180, 182] [52] [**193**, **194**] [**103**, **167**, 102] [**1**, **2**] [**132**, **130**, **131**, **188**, **207**; **210**, **213**, **212**] [**185**] [**112**, 95, 96] [133] [**43**] [**152**, 76] [62] [66] [**144**]	18 (**33**, 15)
	Constantly-engaged	[203] [**136**, 139] [**186**] [**113**]	4 (**3**, 2)
	System-paced	–	0 (**0**, 0)
	Self-paced	[**16**, **127**, 24, 121] [**28**, **29**, **30**, **206**] [**71**, **146**, **148**, **150**] [59] [110] [**27**, **135**] [**187**, **215**, 214] [**201**]	8 (**15**, 5)
Device State Feedback	***Visual***	[**117**] [**75**, **87**, **109**, 183] [**11**, **14**, **13**, 12] [**16**, **127**, 24, 121] [31, 203] [**28**, **29**, **30**, **206**] [**69**, **71**, **105**, **105**, **142**, **146**, **148**, **150**, **163**, **165**, **170**, 114, 180, 182] [52] [59] [**193**, **194**] [**103**, **167**, 102] [**136**, 139] [**1**, **2**] [**132**, **130**, **131**, **188**, **207**, **210**, **213**, **212**] [**185**] [**112**,95; 96] [110] [133] [**43**] [**187**, **186**, **215**, 214] [**201**] [**152**, 76] [62] [66] [**113**, **144**]	25 (**49**, 21)
	Auditory	[**75**, 73]	1 (**1**, 1)
	Multi-modal sensory	[**27**, **135**]	1 (**2**, 0)
***Assistive Device* Type**	***Visual text display***	[**15**, **74**, **87**, **106**] [**149**, **179**] [91] [**98**] [**48**] [**190**] [67]	7 (**9**, 2)
	Speech synthesizer	[**86**] [91] [**98**]	3 (**2**, 1)
	Appliance interface / remote control (wireless, IR, X10 to external devices)	[**33**, **54**]	1 (**2**, 0)
	Limb control neuroprosthetic (FES system)	[**143**, **142**, **164**, **162**, 68, **161**]	1 (**5**, 1)
Device State Feedback	***Visual***	[**15**, **74**, **86**, **87**, **106**] [**33**] [**149**, **164**, **162**, **179**, 68] [**193**] [91] [**98**] [**48**] [**190**] [67]	9 (**14**, 3)
	Auditory	[91] [**98**]	2 (**1**, 1)
	Multi-modal sensory	[**54**] [**143**, **142**, **161**]	2 (**4**, 0)

which design approaches have received little or no attention and, finally, how well designs are reported. Each of these topics is presented in a separate subsection below.

Which Designs Are Comparable?

The main goal of this work was to identify which BI designs can be directly compared to each other. Researchers may choose to compare BI technology designs in terms of many potential factors; Accuracy, response time, throughput, the amount of mental attention required, ease of use or other usability factors such as, physical size and sensor application requirements are a few factors of interest to researchers. Since only technology that performs the same function can be directly compared, we will first discuss comparability of function.

Within the context of the chosen framework, technology comparisons can be made at various levels. BI Transducer designs that produce the same output are directly comparable (regardless of other factors such as bio-recording technology, neurological phenomenon or feature extraction and feature translation methods). For example, all transducer designs producing the same type of 2-state, discrete output can be compared. This principle also applies for direct comparisons of BI technology to non-BI technology like chin switches or eye tracking systems. Likewise, BI Transducer and Control Interface (CI) combinations producing the same output are directly comparable, and could be compared with BI Transducers that produce similar high-dimensional outputs. Systems with Assistive Devices (AD) that perform the same function are directly comparable, where function may be strictly defined as communication via a text display for example, or more broadly defined as communication (or information transfer) in general whether through a text display, drawing tablet, or speech synthesizer for instance. Now what may not be obvious to all readers is that BI technologies can only be compared if they produce the same output (i.e., perform the same function at some level). The focus here is on output and not the other *design attributes*. As stated above, this could be the BI Transducer output, the Control Interface output, the Demo Device output or the Assistive Device output. The other *design attributes* are not important in determining comparability (assuming that the designs are suitable for the target application-an issue that is discussed in the next section). As an example, even though many BI researchers tend to group technology by the bio-recording technology or sensor design (e.g., EEG, ECoG, implanted arrays, or more generally as invasive/non-invasive), the bio-recording technology is irrelevant in determining if two technologies can be compared at a functional level. For instance, an EEG-based transducer can be directly compared with one based on an implanted microelectrode array if the signal processing produces the same type of output.

Within our results we encountered certain types of transducer outputs that are not seen in common interface technologies like keyboards, mice and joysticks. These differences are important to this discussion so we will elaborate on them here. In general, there are three types of transducer output: discrete, continuous and spatial reference – these categories apply to all interface technologies. For brain interfaces, we have recognized that researchers use three types of discrete output, two types of continuous output and ranges of spatial reference output, all of which are unique and thus cannot be directly compared. The first type of discrete output we encountered was in line with our expectation of discrete transducer output. That is, the output signal had one or more states that corresponded to when the user is intentionally controlling the transducer plus a ''do nothing'' or ''idle'' state that corresponded to when the person was in a No Control (NC) state.[22,128] This is the behavior one would expect from standard interface devices such as keyboards and switches. We created the *attribute sub-class* ***discrete (with 1 NC state)*** to refer to this type of output signal. The second type of transducer produced a discrete output that corresponded only to Intentional Control (IC) states, i.e., there was no output state that corresponded to the user's NC state. These transducers assumed that another mechanism would handle the time periods when a user was in an NC state. This type of output is not seen in normal interface devices. We referred to this type of output signal as ***discrete (all IC states)***. The third class of discrete transducer produced an ''unknown state'' in the output to represent periods where the transducer lacked enough evidence (or confidence) to generate an output state classification corresponding to an IC or NC state. We used the *attribute sub-class* ***discrete (with 1 unknown state)*** if there was no NC output state or ***discrete (with 1 unknown and 1 NC state)*** if there was an NC output state. Note, none of the later class was found in the survey set.

For transducers that produce continuous control, there were two general classes of output signal: continuous control relative to a fixed reference (like a volume control on a stereo or a joystick) and contin-

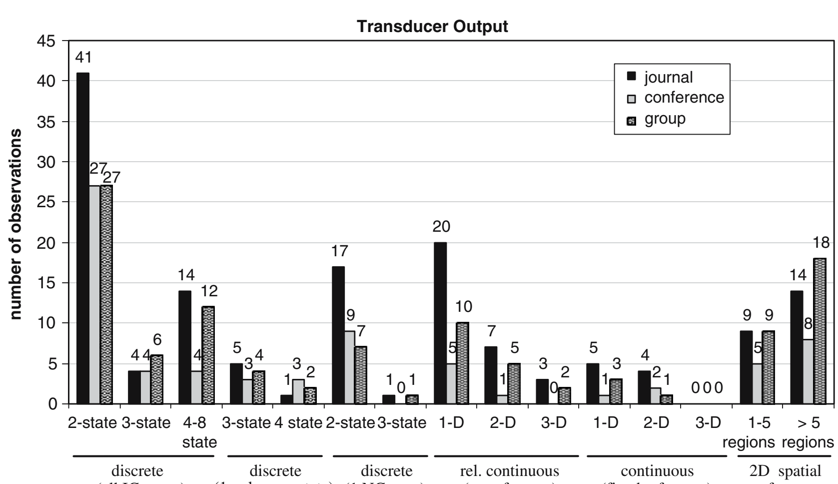

FIGURE 2. Histogram of *BI Transducer* – Output grouped by output category. Refer to text in ''Which Designs Are Comparable?'' Section for definition of terms.

uous control relative to previous values (like the wheel on a wheel mouse or the two-dimensional mouse position control). The first class, which we called ***continuous (fixed reference)***, produces a sequence of absolute continuous amplitude values while the second, which we referred to as ***relative continuous (no reference)***, produces a sequence of relative amplitude changes.

The transducers that produced a ***spatial reference*** (similar to eye tracking, a touchscreen or stylus mechanism), either produced a small number of selectable regions (≤ 5) or a large number of regions (> 10). As such, we arbitrarily grouped these types of transducers into devices that could reference five or less regions and those that could reference more than five regions.

A summary of the number of journal papers, conference papers and research groups related to comparable BI Transducer designs is presented in Fig. 2. From this figure we can see that 27 groups produced 68 designs for ***2-state, discrete (all IC states)*** – 41 of these designs were reported in journals and 27 in conference proceedings. The specific papers are cited in Table 3 under ***BI Transducer*** – **Output** – *discrete (all IC states)-2-state*. All designs in this category are directly comparable. As another example, all 25 transducer designs that produced a ***1-D relative continuous (no reference)*** output are directly comparable. Direct comparison between the transducer designs in the different output categories is either not possible (e.g., discrete versus continuous versus spatial reference) or difficult to test and interpret, such as comparing the designs classified as ***3-state discrete (with 1 unknown state)*** and ***2-state discrete (all IC states)***.

When we switched focus to Control Interface outputs, we observed that all 12 of the designs surveyed produced discrete symbols (alphanumeric characters or commands) and thus are directly comparable even though the underlying transducer, interface paradigm or *CI* translation methods are different. We also see that within the ***Control Interface*** – **Interface Paradigm** attribute, five designs (36%) were based on a ***single, direct selection*** (as in Farwell and Donchin's P300 system menu[48]), three (22%) were ***single, indirect (pointer-based) selections*** (like a point and dwell interface), two (14%) were ***multiple, direct selections*** (e.g., the multi-level menu system proposed by Scherer *et al.*[179]) and four (28%) were ***multiple, indirect (pointer-based) selections*** (like the binary keyboard in Birbaumer's Thought Translation Device[107]).

The Full AT system designs reported in Table 3 made use of the following Assistive Devices (AD): 11 papers (55%) from seven groups reported a ***visual text display***, three papers (17%) from three groups had a ***speech synthesizer***, two papers (11%) from one group presented an ***appliance interface/remote control***, and six papers (17%) from one group reported various designs using a ***limb control neuroprosthetic***. The designs within each of these *AD* categories can be compared and possibly the text display systems could be compared with those that employed a speech synthesizer on a higher-level study of communication ability.

What Technology Designs Have Been Proposed?

From the survey data we can determine what technology designs have been proposed up to January 2006. Due to space limitations, we will restrict the discussion on overall trends with specific examples.

From Fig. 3 we can see that the majority of publications (56%) reported only a BI Transducer design. Of the remainder, 36% reported a *Demonstration System* to demonstrate control with feedback, and only 8% have proposed *Full AT* solutions – 11 (5%) of which used a *3-component system* (Transducer-CI-AD combination) and three (3%) used a *2-component system* (Transducer-AD). Refer to Fig. 1 for system definitions if required.

We can also see from Fig. 4a and b, 166 *endogenous transducer* designs (those driven from internally generated brain activity) were reported by 46 groups. This corresponded to 81% of the ***BI Transducer*** – **Transducer Design Model** *attribute sub-class*. The

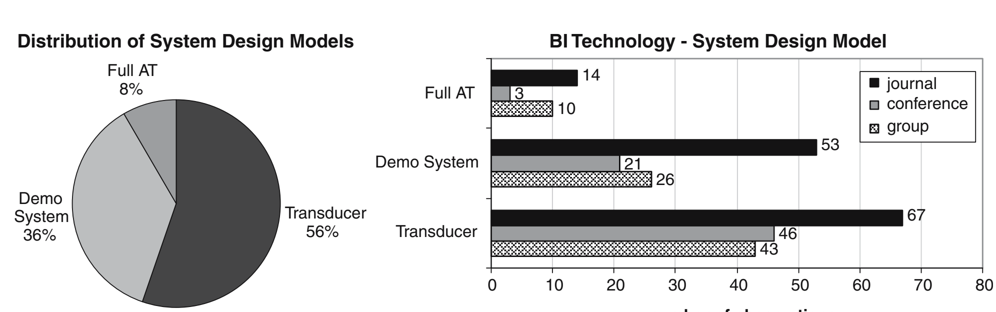

FIGURE 3. Distribution of BI Technology System Design Models.

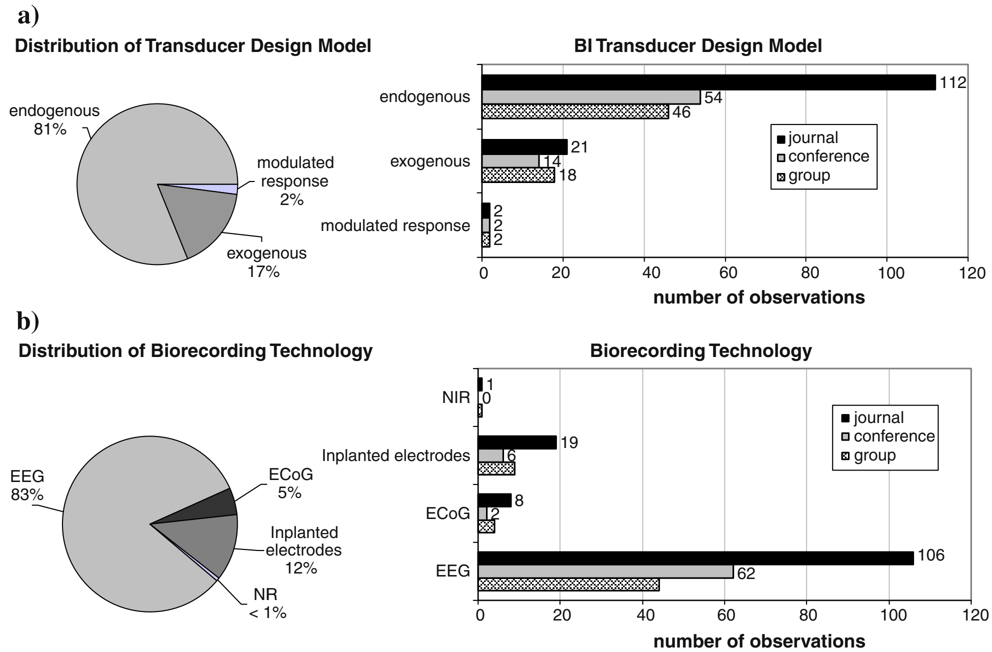

FIGURE 4. Distribution of (a) BI Transducer Design Models and (b) bio-recording technologies.

remainder was 35 *exogenous transducer* designs (those driven from external stimuli to evoke a brain response) from 18 groups contributing 17%, and four *modulated-response transducers* designs (those designs where the user modulated their brain response to external stimuli) from two groups representing the last 2%. None of these design architectures is inherently better than the others. Each has its own merits and the choice of architecture depends on the target application and the type of interactive control required (e.g., direct selection, object positioning or spatial navigation). For instance, *exogenous transducers* have the benefit that no user training is required[43] and they are the only design architecture that offers direct spatial referencing, which is a powerful interaction modality.[129] The down side is they require a constant commitment of a sensory modality[200] and repetitive sensory stimulation (where the long-term tolerance and safety are not yet established). They also must be paired with a Control Interface (such as a menu system) in order to produce a discrete or continuous output which may not be appropriate for many target applications. *Endogenous transducers* can produce discrete or continuous control and do not require an external sensory stimulator. Both are desirable features for many applications. However, the use of spontaneous components of the EEG entails the need to recognize when control is intended and when it is not. These designs also require a certain degree of user training which can range from a few sessions to many sessions spanning several weeks. Certain target applications, such as those with dedicated users, may tolerate long training periods, others, like short term use for out patient rehabilitation, will not. The design architecture used in *modulated-response transducers* provides discrete or continuous control but requires an external stimulator to produce a steady state response in the user's brain which the user modulates to generate control. As these types of output can be provided by endogenous designs without an external stimulator, the benefit of this approach remains to be demonstrated.

As displayed in Fig. 4b, the ***BI Transducer* – Bio-recording Technology** attribute is heavily biased towards EEG (83%) with only 5% on ECoG, 12% on implanted microelectrode arrays, and fraction of 1% on functional Near Infrared. (fNI). When we analyzed this data over time as in Fig. 5, we get a clear view of the predominance of EEG in the context of the field's relatively short history. The relatively large proportion of EEG-based designs compared to more invasive designs and fNI does not represent superior quality of control but rather reflects the relatively low barrier to entry for this older technology (e.g., bio-recording equipment is commercially produced, costs are reasonable and consenting subjects are readily available). The recent increase in more invasive methods, which seem to promise higher-dimensional control, are expected to continue as these technologies are proven to be stable, tolerant and safe and eventually become commercially available. The presence of fNI illustrates how future BI solutions may not be based solely on the

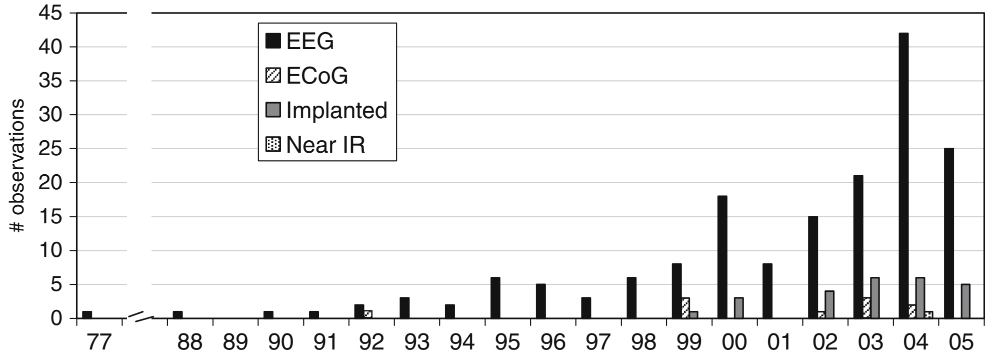

FIGURE 5. Histogram of bio-recording technoloy over time.

measurement of electrical signals, but may include other signals such as metabolic, magnetic, chemical, thermal or mechanical changes related to brain activity as discussed in Ref. [199].

As with the design architectures discussed above, it is impossible to say that a bio-recording approach is superior to another without considering the target application. For example, some researchers may question the practical value of an EEG-based neuroprosthetic that uses external FES device to restores hand grasp function. We would concur if the target application was for permanent functional replacement in a parapalegic with a complete spinal lesion, but not so if the application was to use BI technology to assist the rehabilitation of out patients who were recovering from a stroke.[108] From our perspective, EEG or other externally applied technologies seem the most appropriate choice when the target application is for short-term use (such as the rehabilitation example given above) or where the user, their medical insurer and/or government will not tolerate the costs and risks of implantation. Implanted technologies seem the most appropriate for individuals who require permanent or prolonged functional replacement or augmentation. But there are always special cases and the opinion that really matters is not ours but the end user, their insurer, governments and society in general. This later point was emphasized in many discussions at the BCI2005 workshop on clinical issues and applications summarized in Ref. [108]. This group viewed the appropriateness of a bio-recording technology as a cost–benefit analysis; one that needs to be performed on a case by case basis and will probably change in the future. To illustrate, the costs of implantation (equipment, surgery, user impact, and social impact) are currently large, but imagine if the cost of a technology reduces to a relatively inexpensive day surgery with minimal recovery and the technology is proven to be stable and safe for one's life time. This type of change would shift what people consider appropriate and ethical. Note, our comments assume that researchers will be able to resolve the outstanding technical issues identified by the BI community.[199,211] For EEG, two key issues are user discomfort and application time related to "wet" electrodes. For implanted technology the main issues relate to the stability, tolerance and safety of the recording and transmission electronics.

When we analyzed ***BI Transducer*** – **Output** versus **Neurological Phenomenon** (and the related **Bio-recording Technology**), as depicted in Fig. 6, we can see that overall the most predominant *endogenous transducer* designs are ***discrete (all IC states)*** based on movement related activity (whether temporal movement-related potentials (MRPs), shown as MRP–IM and MRP–AM, or power changes in particular frequency bands, shown as ERD/ERS or rhythm power). Since these observations are biased towards EEG as there were significantly more EEG-based designs in our review set, we can alternatively look within each bio-recording category. Here we see that the EEG, ECoG and fNI designs were predominantly discrete output (which is relatively easier to manifest and qualify) and the few continuous control designs predominantly offered only one-dimensional control. Within the Implanted category, the technology is more uniformly distributed across output type. A few of these papers claimed their continuous control technology produced an absolute continuous value (i.e., a *continuous (fixed reference)* output). However, this type of control is more difficult to manifest, and because many authors did not specifically demonstrate this ability, it was impossible to substantiate the authors' claims. Only the *exogenous transducers* produced a spatial reference output as seen in Fig. 7. These designs were predominately related to a P300 response or steady-state visual evoked potential (SSVEP) response in EEG. Although we cannot predict which neurological phenomenon will be most suitable for a person or activity in general, characteristics such as response time, the

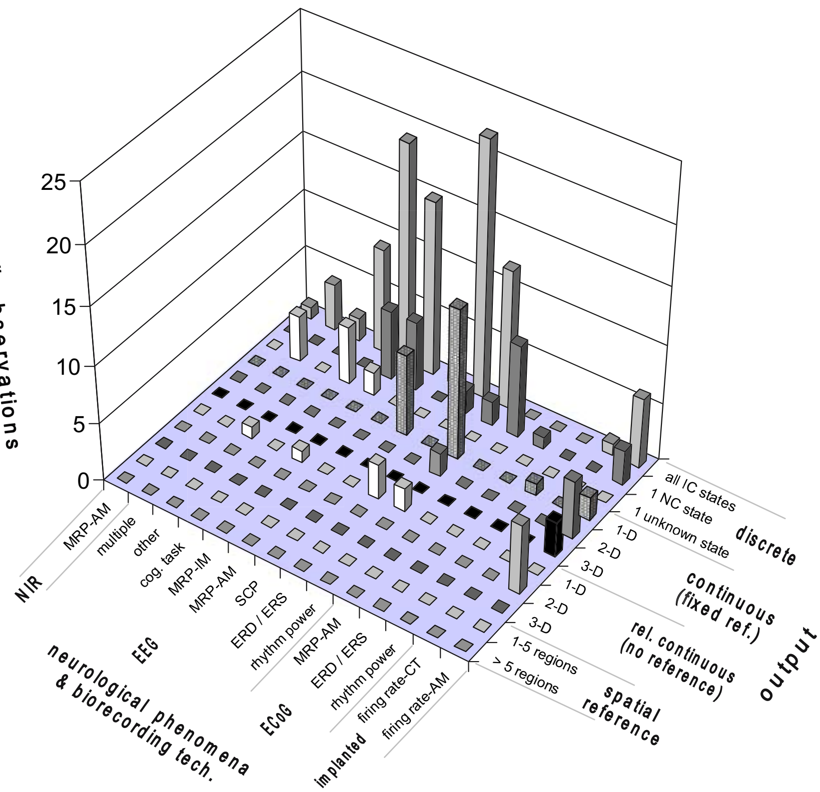

FIGURE 6. Distribution of BI Transducer output for *endogenous transducers* in relation to bio-recording technology and neurological phenomena. In this figure, NIR = Near Infrared, implanted = electrode arrays implanted in the cortex, MRP-IM = Movement-related potentials – imagined movement, MRP-AM = movement-related potentials – attempted movement, cog. task = cognitive task, SCP = slow cortical potentials, ERD/ERD = event-related desynchronization/event-related synchronization, firing rate-AM = cellular firing rate related to attempted movement, firing rate-CT = cellular firing rate related to cognitive task, IC = Intentional Control, NC = No Control state. All other terms are defined in the text.

customization (system training) process and the amount of user training required for a design (attributes not included in the current design taxonomy) all affect the practical usefulness of an approach. For instance, one could not use the current fNI system to control a vehicle as their response time is in the order of 10s of seconds.

The majority of published Control Interface designs, were either ***multiple-selection virtual keyboards*** driven by a one-dimensional pointer (36%) like the binary keyboard in Birbaumer's TTD, or ***single-selection menu systems*** with a spatial reference input (27%) like the menu used in Farwell and Donchin's P300 system. All produced an *N-state, discrete* output (translating *continuous control* or *spatial reference* inputs into *N-state, discrete* output values). There is a wide variation in Control Interface design and most designs do not seem based on existing interface design principles.[51,147,189] This issue requires further attention. Also, only a few research groups have proposed a method for an On mechanism[33,86] or discuss the use of error correction[158,194] – both of which are important issues for real world BI AT.

Within the ***Demo Device*** category, we see in Fig. 8 that the majority of papers employed a computer monitor with a range of virtual objects under control: 40% with ***cursor*** (eight groups), 1% with ***cursor + discrete functions*** (similar to a mouse) (1 group), 23% with ***virtual world*** (seven groups), 12% with ***discrete indicator*** (four groups), 10% with ***menu system*** (six groups), 9% with ***level indicator*** (three groups), and 3% with some ***other*** type of device (one group). The rest presented some form of physical device: 27% with ***vehicle simulator*** (one group), 18% with ***model vehicle*** (one group), 18% with ***robotic arm/hand*** (two groups), and 36% with some ***other*** type of device (three groups). The dominance of ***cursor*** control as a demonstration was not unexpected as many groups are looking to develop a computer interface. The observed ***Demo Device*** – **Type of Control** attribute broke down into 47% ***direct selection***, 8% ***continuous value adjustment***, 1% ***indirect selection*** and 44% ***object positioning***. We found the breakdown of ***object positioning*** informative. We had identified four main types of ***object positioning***, defined with increasing difficulty: (1) ***move object from fixed starting***

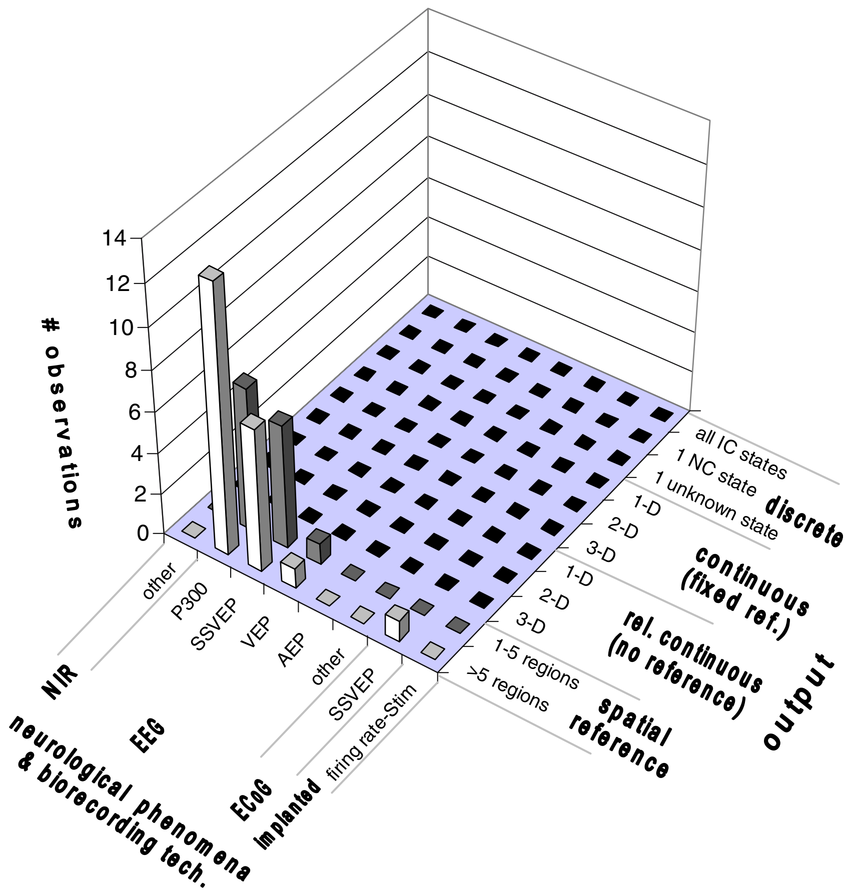

FIGURE 7. Distribution of BI Transducer output for *exogenous transducers* in relation to bio-recording technology and neurological phenomena. In this figure, NIR = Near Infrared, implanted = electrode arrays implanted in the cortex, P300 = P300 response, SSVEP = steady-state visual evoked potential, VEP = visual evoked potential, AEP = auditory evoked potential, firing rate-stim = cellular firing rate related to external stimulation, IC = Intentional Control, NC = No Control state. All other terms are defined in the text.

point(s) to 1 target per trial (in 1, 2 or 3D), (2) ***move object from fixed starting point(s) to 1 of N possible targets***, (3) ***continuous positioning (path not important)***, and (4) ***continuous path following/ navigation /drawing (where path is important)***. The first type, which was used in the majority (50%) of these types of demonstration systems, exhibits basic control, but the reported error rates are optimistically exaggerated as there is no potential for moving to a wrong target. Also there is no practical use for this type of interaction, thus these types of demonstrations should be limited to initial proof of concept studies.

To conclude this discussion, we will say a few words on which of these technologies are compatible. For components to be compatible, the input of one component must match the output of another. As an example, all five of the Control Interface designs require an input signal of type ***1-D relative continuous (no reference)***. These are compatible with the 25 BI Transducer designs that produce the same type of output. Many other examples can be extracted from Table 3. This ability to identify compatible technology has the potential to increase cross-fertilization of technology between research groups.

Which Target Applications Have Been Pursued?

Of the papers that reported **Target Population**, 99% of the designs were targeted at individuals with some form of severe motor disabilities, some reports being more specific, e.g., 56% were targeted at individuals with paralysis (40% specified full paralysis, 2%, partial paralysis and 14% unspecified). Less than 1% of designs were aimed at able-bodied individuals (viz., pilots).

The papers that reported a specific **Target Activity** were focused on ***communication with people*** (15%), ***control of appliances*** (15%), ***control of paralyzed limbs*** (12%), ***control of vehicle*** (1%), ***personal mobility*** (1%) or ***control of objects in virtual reality*** (< 1%). The majority (56%) of papers were particularly vague about their target activity. Most papers simply

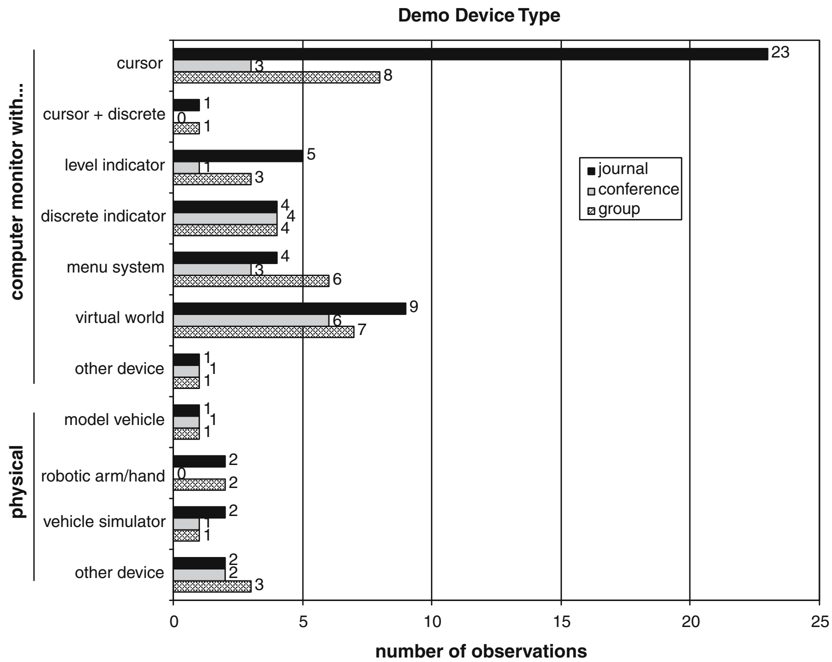

FIGURE 8. Distribution of demo device type.

included wording such as "BCIs are a device for communication and/or control" and did not indicate a specific activity. Although we have recorded all these papers as if they are targeting a general solution, we suspect that several of the authors have not given this aspect much consideration and treat the development of BI technology as an academic challenge with no real connection to their target community. This is a vulnerable position for this research community as funders have limited patience and may eventually withdraw support if real, practical solutions that address people's needs do not begin to emerge.[108,199]

Which Design Approaches Have Received Little or No Attention?

Several of the *attribute sub-classes* shown in the above figures or tables had few or no observations. These approaches are potentially opportunities for technology advancement.

One of the most notable opportunities is the use of implanted technologies for *exogenous transducers*. *Exogenous transducers* produce a valuable mode of interaction: direct spatial referencing. Given the relative success with EEG-based *exogenous transducers*, one would expect greater accuracy and resolution from an implanted system as seen in Ref. [190]. Combining this with a switch (discrete transducer) with NC support one could have a powerful point-and-click interface.

Within EEG-based *exogenous transducers*, there are many configurations of stimulation mechanism parameters that have not been tried. Alternative designs may provide increased response to a stimulus, resulting in higher recognition accuracy. The reader is directed to Ref.[129] for a more detailed discussion of stimulation mechanism configuration and examples.

Another important area that has not received much attention is the development of transducer designs that support No Control (NC) (the times when a user is not intentionally controlling the BI). This is a critical design feature as lack of NC support precludes self-paced (or asynchronous) AT operation, which is the most natural mode of interaction. Although the number of BI Transducer designs with NC support has grown modestly over recent years, more effort is required before we can claim to have useful, self-paced operation.[128]

In designs using field potentials, artifacts, particularly ocular, movement and muscular (electromyographic, EMG), can often disrupt or confuse a transducer. Given that this is a recognized problem in signals from externally applied sensors,[199] it is surprising that less than 8% of the reported articles utilize some form of artifact processing and fewer actually demonstrate how well their artifact processing methodologies work. The lack of artifact processing or the use of a particular processing method is a major issue that may render a particular transducer design useless in real-world settings, and as such this issue deserves more attention from those working with externally applied sensors.

Although a few people have demonstrated 2-D or 3-D continuous control (where the movement path is not important), no one has reported continuous path following (where the path is important). This type of control is needed for drawing and navigation, which are powerful, highly desirable abilities, and should be attainable given the reported abilities of some of the 2- and 3-D continuous controllers. All that seems to be missing is for researchers with this technology to demonstrate this ability.

One last item would be the On mechanism. Only two groups have attempted to build an On mechanism into their AT. Much more work is needed in this area if the community is to realize useful, unsupervised assistive technology.

Many additional areas have not been pursued, and will probably be pursued only if the current approaches prove to be fruitful. Examples include (1) more complex Demo Devices and Control Interfaces, (2) targeting individuals with inconsistent motor control, such as cerebral palsy (CP) or multiple sclerosis MS, (3) targeting activities such as body control (posture, bladder), and (4) building BI Transducers that produce higher dimension outputs.

How Well Are Designs Reported?

The majority of the papers reviewed were found in journals and conference proceedings of a technical nature. This was not an unexpected result considering that much of the research in the BI area is still in an early technological development stage.

Overall, we were able to interpret the general technical characteristics of a design most reports, enough to categorize the designs using our classification template. However, many of the papers lacked significant detail on the signal processing methods that precludes replication of their work. This was not an issue of lack of common vocabulary and methods but rather a lack of full reporting. It is a serious scientific issue that the BI community needs to address quickly in order to establish and maintain rigor within this maturing field.

In general, the ***Target Application*** attributes (**Target Population**, **Target Activity** and **Target Environment**) were not well reported: 34% of **Target Population**, 17% of **Target Activity**, and 97% of **Target Environment** were not reported. The relatively poor reporting of targets is an important oversight in these works since the usefulness of a design cannot be interpreted or challenged without an explicit definition of the target application.

BI Transducer – **NC Support** was also poorly reported – 88% of papers did not report this attribute. Most of these papers were testing ***BI Transducer*** – **Outputs** in a ***synchronized*** test environment and as such overlooked the need to test and report how well their transducer designs functioned when a user was in the No Control (NC) state. Many may dismiss this as unimportant, but even in synchronized control environments one can not guarantee the user will always be in an Intentional Control (IC) state during the system-defined windows of control, especially in real-world (unsupervised) settings. As such, all BI Transducers should be evaluated and their response to NC reported in order to understand what types of errors can be expected from a proposed design.

Finally, there was confusion around the use of the terms "motor imagery" and "imagined movements" in the literature. From the surveyed papers, "motor imagery" or "imagined movements" was used on one hand to describe a type of mental activity in able-bodied subjects. In these cases, the subjects were likely using some form of motor imagery – although the experimental protocols rarely reported the specific controls (such as structured questionnaires) to ensure that the subjects were doing as requested. These terms were also used to describe a mental activity in individuals with severe movement disabilities, although with the lack of reported controls, it was possible that these people were actually using attempted movements instead of imagery. As attempted movements are different neurological mechanisms then imagining movement, it would help if the field could clarify the use of these terms and use appropriate controls to ensure subjects are using the neurological mechanism requested.

CONCLUSIONS

We have completed the first comprehensive survey of BI technology designs published up to January 2006. The results of this survey form a valuable, historical cross-reference from which we have discussed the following points: (1) which technologies are comparable, (2) which technology designs have been proposed, (3) the application areas (users, activities and environments) targeted by researchers, 4) the design approaches which have received little or no attention, which are possible opportunities for new technology, and 5) how well designs are reported. We have also demonstrated that this type of meta-analysis of BI design is possible and produces information that is valuable to the field.

This work directly addresses the need for methods to identify comparable technology. Like other AT, typical studies of BI technology cannot be evaluated using classical means with a "no treatment" control group due to factors such as high subject variability, small number of subjects, uncontrolled experimental factors (unbalanced subject groups); and functional limitations of the target population. As such, identifying superior technology can only be achieved by directly comparing BI technologies to each other within the same test environment. The presented results not only allow researchers to determine which BI technologies can be directly compared in this way, but it also illuminates which non-BI technologies may be compared as well.

In many ways, the discussion of the results presented is a sample of the type of analysis that can be performed. There are many other types of analysis that could be conducted, particularly analysis across multiple attributes, attribute development over time, and technology developed within a specific research group. A possible extension of this work may include an on-line design database that would allow the community to directly access these survey results and perform their own analysis.

One of our hopes is that this study will spawn further discussion of theoretical formalisms, leading to improved (and possibly multiple) models and taxonomies for BI technology. The *attribute subclasses* defined in Table 3, for instance, represents a proposal of subcategories, not a final set, and we encourage others to revise or expand this initial set. For example, we have previously mentioned the opportunities to add *design attributes* related to customization, user training and response timing to the design taxonomy. Other examples include adding *attribute sub-classes* to more clearly delineate target populations or expanding the **Feature Extraction** and **Feature Extraction** *design attributes* to capture the increasing diversity of signal processing methods being reported.

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APPENDIX A: IDENTIFIED RESEARCH GROUPS

Table 4 lists the research groups used in this study identified by the last name of one principal investigator (PIs) from each group. For multi-institution projects, multiple PIs were listed. PIs were selected based on our knowledge or, for groups that were unfamiliar (marked with an * in the table), the last author from the reviewed papers was used. Affiliated

TABLE 4. Research groups used in this study. IDs marked with a * indicate research groups that were unknown to the authors and the principal investigator ID was assumed to be last author from reviewed paper(s).

ID	Affiliation/Project
Anderson, C	Department of Computer Science, Colorado State University, Fort Collins, CO, USA.
Andersen, R.	Division of Biology, California Institute of Technology, Pasadena, CA, USA.
Aunon	Department of Electrical Engineering, Colorado State University, Fort Collins, CO, USA.
Babiloni	Human Physiology Institute, University "La Sapienza", Rome, Italy.
Bayliss	Rochester Institute of Technology, Rochester, NY, USA.
Birbaumer	Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Tübingen, Germany.
Birch	Neil Squire Society, Vancouver, BC, Canada.
Borkowski*	Applied Science and Engineering Laboratories, A.I. duPont Institute, Wilmington, DE, USA.
Cabral*	Department Telecommunications and Control, Escola Politécnica, São Paulo University, São Paulo, SP, Brazil.
Donchin	Department of Psychology, University of South Florida, FL, USA
Donoghue	Cyberkinetics Neurotechnology Systems, Inc., Foxborough, Massachusetts, and Department of Neuroscience, Brown University, Providence, RI, USA.
Erfanian*	Department of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran.
Gao, S.	Department Electrical Engineering, Tsinghua University, Beijing, China.
Garcia	Swiss Federal Institute of Technology, Lausanne, Switzerland.
Glassman*	Department of Electrical Engineering, Massachusetts Institute of Technology
Huang*	Institute of Biomedical Information and Control, Huazhong University of Science and Technology, Wuhan, China
Hsieh	Department Medical Research and Education, Taipei Veterans General Hospital, Taipei, Taiwan.
Inokuchi	Graduate School of Engineering Science, Osaka University, Osaka, Japan.
Kennedy	Deparment of Neurosurgery, Emory University School of Medicine, Atlanta, GA, USA.
Kipke	Department of Biomedical Engineering, University of Michigan, Ann Arbor, MI, USA.
Kostov	Faculty of Rehabilitation Medicine, University of Alberta, Edmonton, AB, Canada.

TABLE 4. Continued.

ID	Affiliation/Project
Levine	Department of Physical Medicine and Rehabilitation and Department of Biomedical Engineering, University of Michigan, Ann Arbor, MI, USA.
McDarby	Department of Electronic Engineering, National University of Ireland Maynooth, Kildare, Ireland.
McGinnity*	Department of Engineering, Magee Campus, Univ. Ulster, Northern Ireland.
McMillian	Fitts Human Engineering Division, Armstrong Laboratory, Wright-Patterson Air Force Base, OH, USA.
Meng*	Department of Electrical Engineering, Stanford University, Stanford, CA, USA.
Millan	Dalle Molle Institute for Perceptual Artificial Intelligence, Martigny, Switzerland.
Moran	Department of Biomedical Engineering, Washington University, St. Louis, Missouri, USA
Morradi*	Department of Biomedical Engineering, Amir Kabir University of Technology, Tehran, Iran.
Muller	Fraunhofer, FIRST (IDA), Berlin, Germany
Nakashima*	Faculty of Medicine, Tottori University, Yonago-city, Japan
Nicolelis/Chapin/Principe	Collaborative project between Department of Neurobiology, Duke University, Durham, NC, USA, Department of Physiology, State University of New York, Downstate Medical Center, Booklyn, NY, USA, and Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL, USA.
O'Leary*	Department of Organismal Biology and Anatomy, University of Chicago, IL, USA.
Pfurtscheller	Institute of Biomedical Engineering, University of Technology Graz, Graz, Austria.
Pineda	Department of Cognitive Science, University of California, San Diego, La Jolla, CA, USA.
Qin*	Institute of Automation Science and Engineering, Southchina University of Technology, Guangzhou, China
Reilly	Department of Electrical Engineering, National University of Ireland, Dublin, Ireland.
Ritter*	Faculty of Technology, Neuroinformatics Group, Bielefeld University, Bielefeld, Germany.
Roberts/Penny/ Stokes/Curran/Owen	Department of Engineering Science, University of Oxford, Oxford, UK, Wellcome Department of Imagin Neuroscience, University College London, London, UK, Research Department, Royal Hospital for Neuro-disability, London, UK, MRC Cognition and Brain Sciences Unit, University of Cambridge, Cambridge, UK, Dept. Law, University of Keele, Keele, UK.
Rosa*	LaSEEB–ISR– IST, Lisboa, Portugal.
Saiwaki*	Department of Systems and Human Science, Graduate School of Engineering Science, Osaka University, Osaka, Japan.
Schwartz	Department of Neurobiology, University of Pittsburgh, Pittsburgh, PA, USA.
Seung*	Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA.
Shahabi*	Department of Computer Science, University of Southern California, CA, USA.
Sohn*	Department of Psychology, Chungnam National University, Taejon, Korea, and Electronics and Telecommunications Research Institute, Taejon, Korea.
Sundaresan	Department of Electrical and Computer Engineering, University of Houston, TX, USA.
Sutter	The Smith-Kettlewell Eye Research Institute, San Francisco, CA, USA.
Trejo	NASA Ames Research Center, Moffett Field, CA, USA.
Vicente*	Department of Electrical and Computer Engineering, Florida International University, Miami, FL, USA.
Vidal	Department of Computer Science, University of California Los Angeles, CA, USA.
Wilson*	Department of Electrical and Computer Engineering, University of New Hampshire, Durham, NH, USA.
Wolpaw	Wadsworth Center for Laboratories and Research, Albany, NY, USA.
Yom-Tov	Department of Electrical Engineering, Technion, Israel Institute of Technology, Haifa, Israel.

institutions or projects are listed as the PIs latest published affiliation. (Our intent here is to provide a quick reference identifier for each group and this list is not meant as an accurate representation of principal investigators for these institutions or projects. We recognize that over time, researchers may change institutions from the ones listed).

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