BRAIN-COMPUTER MUSIC INTERFACING – CURRENT APPROACHES AND PROSPECTS

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Brain-computer music interfacing (BCMI) is a field of research addressing the idea that electrical oscillations within the brain can be used to generate or manipulate music, or support a musical activity. This is achieved by transmitting brainwave activity expressed as electrical frequencies using electroencephalogram (EEG) electrodes placed upon the scalp to a computer which maps or translates this input to audible output with musical structures or rules (Miranda, Castet 2014; Rosenboom 2014). The concept of using this rhythm rich EEG signal for musical applications has led to the emergence of new types of musical instruments, interactions, performances and experiences which have captured the imaginations of many artists and technologists (Miranda 2006a, 2006b).

What is BCMI?

The term BCMI was coined by Eduardo Reck Miranda, and stemmed directly from adopting brain-computer interfacing (BCI) technology for supporting musical activity (Miranda 2006a, 2006b; Miranda, Castet 2014). Figure 1 illustrates the schematics of a BCMI in terms described by Miranda. Systems such as these are made up of the following steps:

1. Audio/Visual Stimuli (optional): this is present in some systems where audio or visual stimuli other than the audio output can function as additional feedback or as part of controlling the system.

2. EEG Input: EEG signals recorded via electrodes placed on the scalp.

3. Signal Processing: amplification and data analysis to isolate and extract meaningful information for further classification or processing depending on the system design.

4. Transformation Algorithm: maps the EEG data to musical parameters, such as MIDI data.

5. Musical Engine: receives musical parameters as input commands for musical audio output.

The way audio output expresses brainwave activity is dependent on the design and components of the BCMI system. There is currently no standard configuration of hardware or software – all BCMI systems described by the literature have been designed differently according to their purposes, limitations and validation methods. Types of BCMI systems and prevalent methods for achieving the steps illustrated in Figure 1 will be described in detail later in this text.

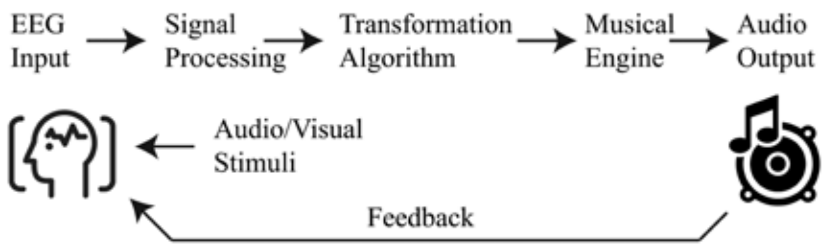

Figure 1. Steps of a typical BCMI system (adapted from Miranda, Castet 2014: 227)

Background and State-of-the-Art

The first person to record electrical brainwave activity was Hans Berger in 1924 (Berger 1929; Adrian et al. 1934; Miranda 2006a, 2006b), which led to the development of EEG technology as a tool for diagnosing neurological disorders such as epilepsy (Buzsáki 2006; Nunez, Srinivasan 2006). The first person to propose using the EEG as a method for interfacing with machines was Jaques Vidal in 1973 (Vidal 1973; Gürkök, Nijholt 2013; Wadeson et al. 2015). The first person to use the EEG to create music was the composer Alvin Lucier in 1965 by directly applying his amplified brainwaves to an array of percussion instruments (Christopher et al. 2014). He was closely followed by other composers and musicians seeking to harness the EEG for music, including David Rosenboom's research in which he searches for potentially useful data in the EEG for music making (Rosenboom 1999; Väljamäe et al. 2011). Since then, progress in this field has been made in step with technological developments and limitations in biomedical engineering, neuroscience, and computer technology (Miranda, Castet 2014).

Four major challenges in the field of BCMI are therefore closely related to choices made while putting together a system that can actualize the steps described in Figure 1:

- first, designing and accessing the configuration of hardware components necessary;
- second, the isolation of EEG information meaningful for control;

- third, the development and implementation of a chosen mapping strategy for generating or manipulating music;
- and fourth, defining ways that this technology can be applied to meeting needs in therapy and in improving lives (Tan, Nijholt 2010; Miranda, Castet 2014).

The inconsistency of methodology which can be observed in the literature, however, is typical of newly developing research areas – it is a novel and exciting, deep theoretical space where the research communities involved are enthusiastic but diasporic.

Types of BCMI Systems

Despite the wide variety of BCMI systems described in the literature, Miranda notes that, with respect to the historical development of this research field, such systems can be classified into three categories (Miranda, Castet 2014) presented in Table 1:

Table 1. Types of BCMI classified by technique

Type of Technique	Description
EEG sonification	Conversion of EEG data into sound for analysis in non-musical domains, such as in medicine, where listening to the EEG signal is a tool for analysis or diagnosis of specific mental states or conditions.
EEG musification	Mapping EEG information arbitrarily to musical parameters, with limited control or efficacy.
BCI control	Direct, real-time cognitive control of music is inherent to the system design.

The techniques described above are dependent on any given system's technical limitations and are often chosen to best serve research goals. Thus, BCMI research can also be classified according to research communities. Table 2 describes two major types of research community in terms of their aims, and main application areas (Tan, Nijholt 2010; Miranda, Castet 2014).

Table 2. Types of BCMI research communities

Research Community	Humanities	Scientific
Aims	To use BCMI for musical performance, composition, instrument design, and new collaborative or interactive musical experiences.	To use BCMI for music therapy, testing music psychology or neurophysiological hypotheses, developing better technology through evaluating the performance of configurations within their focus.
Applications	• Playing musical instruments or manipulating interactive musical systems with thoughts. • Composing music by selecting notes, fragments or textures stored within an interactive system. • Participating in individual or collaborative control of musical parameters such as pitch, dynamics, timbre and tempo. • Generating audio/visual stimuli to support a musical activity such as performance, or interactive installation.	• Neurofeedback training for persons and circumstances where learning to control mental states at will is beneficial to health or well-being, such as in treating depression. • Enabling people who cannot play musical instruments to experience the social benefits of collaborative music making, such as to provide a means for self-actualization for shut-in cases where bodily movement is limited. • Environmental control, such as selection of music based on mood or desired mood.

Humanities, research communities, music psychologists and musicologists call for more embodied approaches which take into account the multi-faceted nature of musical interaction including the individual's musical experience, the corporeal aspect of musical activity, as well as the physical and socio-psychological environment (Cross 2005; Juslin 2005; Large 2008; Leman 2008, 2010; Overy, Molnar-Szakacs 2009; Hargreaves et al. 2011; McGuiness, Overy 2011; Rocchesso 2011; Gill 2012; Giacomo, Keller 2014; Keller et al. 2014; Reidsma et al. 2014; Haumann 2015; Laroche, Kaddouch 2015; Volpe et al. 2016). Literature reporting in the area of artistic BCMI research is thus often more concerned with evaluating the aesthetic result of the system's output than documenting aspects useful for replicating or carrying forward their approaches. This is partly a result of EEG technology still being relatively expensive and difficult to obtain today – the artistically inclined therefore often rely on consumer grade EEG devices where the technical processes such as signal extraction, analysis, classification and computer actuation are in great part defined by algorithms built into the product (Maskeliunas et al. 2016). Bypassing these technical processes often results in highly creative solutions albeit under-informed by the underlying sciences, thus lacking reliable data for practical use. Some examples of the leading commercially available brain activity monitoring systems to date are made by Emotiv, MindMedia, Neurosky, Enobio, iMotions, and Muse[1]. Thus, BCMI for artistic research has become an uneven but spontaneous playing field where new ideas are rapidly born and manifest into unique proof-of-concept musical experiences, but are rarely useful for making further advances.

[1] See respectively the webpages *Emotiv*, *MindMedia*, *Neurosky*, *Neuroelectrics* [*Products / Enobio*], *iMotions*, and *Muse* (a full description is provided in the list of references at the end of the article).

Because its aims are aligned to medical applications, the scientific research community calls for more rigorous assessment of methods, clinical grade equipment, and detailed reportage for scientific validation of their results. For research to be of practical use in a certain community, the scientific community calls for detailed documentation describing the following parameters (Hermann 2008):

- equipment technical details: electrodes, amplifier models and computer hardware;
- electrode placement, channels and referencing technique used (e.g. a 10–20 electrode system);
- EEG temporal resolution or sampling rate (e.g. 250 Hz);
- pre-filtering of low and high pass frequencies;
- details of the signal processing (e.g. block or window size: fast Fourier transform, or FFT);
- reduction of artefacts;
- EEG features selected for sonification (e.g. relations or objective properties of amplitude);
- musical parameters selected for generation or manipulation, and how this is precisely related to the EEG input (e.g. mapping musical output tempo to average alpha power from a single electrode).

However, imposing strict methodological controls often results in disembodied musical interactions, far removed from socio-cultural contexts where musical experiences take place in every-day life (Leman 2010). Commentary on the research space found in the literature suggests that this gap can be closed by encouraging closer collaboration between these communities (Leman 2008; Miranda, Castet 2014). Future research is often encouraged to systematically compare different BCMI configurations, methods, and mappings, and challenged to conduct research in embodied musical contexts in order to be adopted and applied in the real world.

The section to follow examines current approaches to BCMI, describing in greater detail the materials and methods for obtaining an EEG signal, processing and extracting features from that signal, and transforming it into data which can be mapped for musical control (see Figure 1).

Approaches to BCMI

BCMI systems rely on EEG technology, which has been developed and informed by neuroscience mainly for the purpose of determining functional brain activity and diagnosing neural disorders (Miranda 2006a, 2006b; Nunez and Srinivasan 2006; Rosenboom 2014). More recently, EEG research has explored many new methods for detecting mental processes, commands, states, as well as levels of arousal, attention and emotion by charting neural activity represented as frequencies over time (Hondrou, Caridakis 2012; Maskeliunas et al. 2016). Music itself can modulate these mental dimensions, and it also exists in the frequency-time domain. Both brainwaves and music can be represented as frequency over time, and this fundamental similarity seems to promise great potential for meaningful translation. The EEG signal has a densely rhythmic quality, which it lends itself well to translation into musical parameters. One need only filter away the noise and isolate the rhythms to assign controls to. This process is at the heart of every BCMI system, and the equipment and methods used are of great importance to the type of validation their designs seek. The following sections examine approaches to BCMI by describing the technology and techniques employed at each stage of the process from recording EEG input to audio output.

The EEG Method for BCMI

To aid comprehension of the later material, this section is dedicated to relaying foundational knowledge on the EEG method relevant to BCMI. The temporal resolution of the EEG method is in the millisecond range (Berger 1929; Buzsáki 2006), making it the most practical choice among other functional neuroimaging methods such as PET, MEG, or fMRI for BCMI applications which require real-time feedback for a sense of intentional control. In BCMI applications, this signal is processed by software that maps the information for musical output determined by the musical engine described in Figure 1. The first stage of a BCMI system is therefore acquiring an EEG signal using electrodes placed on the scalp. Collectively, the data gathered from all the electrodes is referred to as the EEG signal, which represents neural activations expressed as oscillations of electrical potential that can be analyzed in a number of dimensions (Buzsáki 2006). Each electrode is referred to as a channel, and a standard configuration is known as the 10–20 electrode system (Jasper 1958; Niedermeyer, da Silva 2005; Sanei, Chambers 2007), though more channels are possible. Figure 2 illustrates the locations of electrodes using the 10–20 configuration.

Different regions in the brain have different specializations, thus the locations of the electrodes are significant for detecting specific neural activity from specific areas (Buzsáki 2006; Nunez, Srinivasan 2006; Tatum et al. 2007). The electrodes are named after the cortical area they are located: F for frontal, C for central, P for parietal, and O for occipital. Even numbers follow the letter prefix for locations on the right hemisphere, while those on left hemisphere are followed by odd numbers. The letter ‘z’ follows locations on the top of the head, directly between hemispheres (Tatum et al. 2007; Miranda, Castet 2014). However, the spatial resolution of the EEG is relatively low compared to other methods, and the data can represent several coordinated networks (Buzsáki 2006).

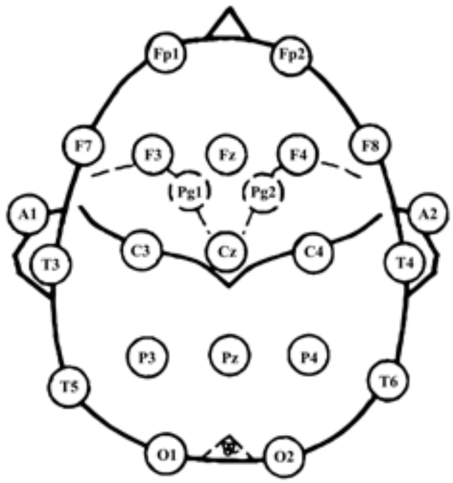

Figure 2. The international 10–20 system configuration for EEG electrode placement (adapted from Niedermeyer, da Silva 2005: 140)

The skull attenuates the electrical signal and as a result, its amplitude is very low, at approximately 100 μV (Malmivuo et.al. 1995: 257). To address this, conductive gel is usually applied to each electrode, and wires deliver the signal to an amplifier, before being digitized by a computer. The need for conductive gel and wires has been an obstacle for EEG technology in becoming practical for BCMI applications which typically call for portability, fast set-up times, and freedom of body movement.

Recent developments in EEG technology have given rise to more affordable and portable devices, and some are now able to measure a useful range of parameters applicable to BCMI systems widely accessible for consumer purchase (see Footnote 1). Some of these have overcome the aforementioned challenges by incorporating dry electrodes and wireless transmission. At present, consumer grade devices used in documented BCMI applications often have limited reliability, and customisability relies on expertise in computer science and advanced mathematics (Maskeliunas et al. 2016). However, these products are constantly improving and have been used in a growing number of peer-reviewed studies (Ramirez, Vamvakousis 2012; Levicán et al. 2017). As aforementioned, using the EEG for BCMI involves processing the raw electrical signals and mapping these to musical parameters. The following sections describes these steps in further detail.

Aspects of EEG Signal Processing

The first step in processing the EEG signal is noise reduction. Noise mainly results from muscle artefacts, interference from electrical power lines, and other exogenous sources of electromagnetism, and is not relevant to the input (Tan, Nijholt 2010; Hondrou, Caridakis 2012; Miranda, Castet 2014; Wadeson et al. 2015). Noise is normally reduced using digital filters, for example, computer software during digital conversion. For example, electrical interference from power lines typically occur in the 50–60 Hz range depending on the power supply, so a narrow band filter may be applied to that range to reduce noise in the signal (Tatum et al. 2007). When using a standard electrode configuration like the 10–20 system, two reference electrodes are normally attached to the earlobes and a grounding electrode attached anywhere on the body. Signals from the reference electrodes represent electrical information which does not originate from cerebral activity, and is thus identified as noise to be subtracted from the signals originating from the active electrodes on the scalp. Similarly, the grounding electrode is connected to the ground circuit in the amplifier, which allows the computer to filter out electrical noise originating from the amplifier and other nearby electronic systems (Teplan 2002; Nunez, Srinivasan 2006).

Digital conversion uses sample rates which are also expressed in Hz, indicating the number of data points recorded per second. For example, for research and clinical use, sample rates normally range between 250 Hz (4 milliseconds) and 2000 Hz (0.5 milliseconds), though rates up to 20,000 Hz (0.05 milliseconds) are technically possible (Tan, Nijholt 2010). Additionally, high pass and low pass filters are applied to frame the window of frequencies being measured (Nunez and Srinivasan 2006). On a computer, a typical EEG signal display window represents digitized signals from individual electrodes as sinusoidal waveforms revealing amplitude plotted over time. Various artefacts can be observed in these signals caused by non-cerebral sources.

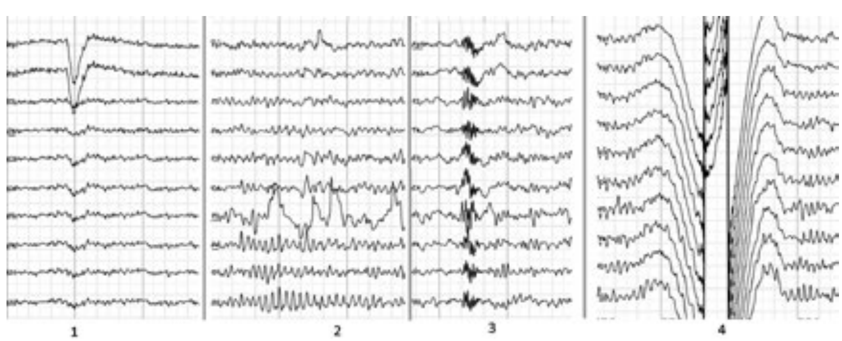

Figure 3. Four common artefacts in the EEG signal displayed as digitized waveforms (Cherninskyi 2015)

An example of a typical EEG display is shown in Figure 3, revealing four common types of artefacts which are normally removed as part of the signal processing stage (Nunez and Srinivasan 2006; Tatum et al. 2007; Lopata 2014). Number 1 represents eyeball muscular excitation, such as blinking. Number 2 shows an artefact on channel P3 and is the result of a bad contact between the electrode and the scalp at that location. Number 3 is an artefact resulting from the act of swallowing. Number 4 shows an artefact caused by a bad contact between the reference electrode and the skin.

The EEG waveforms shown in Figure 3 simply reflect the raw data input from each electrode before any transformation algorithms are applied for feature extraction. One can observe from this representation that EEG processing fundamentally takes place in the time-frequency dimension, the level of amplitude dimension, and the spatial dimension. The entire available EEG spectrum can range from 0 Hz to up to half of the sampling rate, but research typically has focused on frequencies between 0.5–50 Hz, as this is the range relevant to neural activity ranging from deep sleep to highly engaged waking activities such as in sports or music. Measurements outside of this window are rare as activity above and below are difficult to distinguish from artefacts. In clinical practice, this range has typically been divided into five categories or bandwidths relevant to types of mental activity or states, illustrated in Figure 4 (Nunez, Srinivasan 2006; Tan, Nijholt 2010; Lopata 2014).

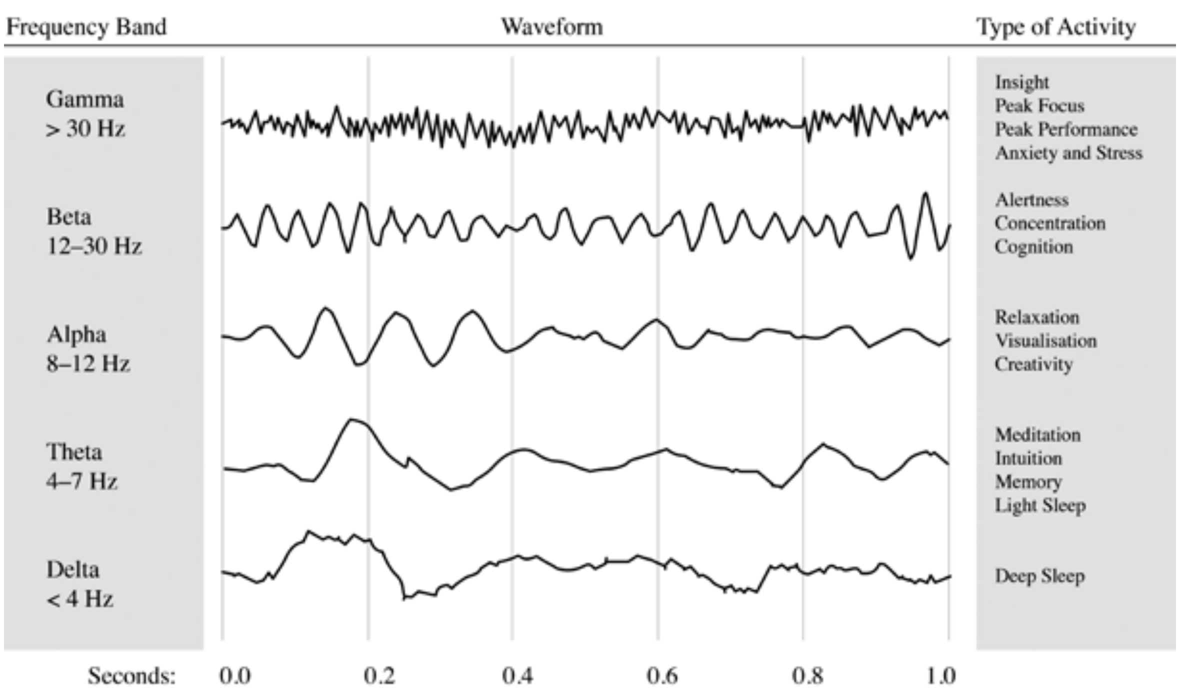

Figure 4. Typical frequency band divisions of the EEG spectrum and associated mental activity (adapted from Tan, Nijholt 2010: 207)

So far, we have seen how EEG signals are recorded, measured and represented for analysis for clinical use, but for BCMI applications the ranges described in Figure 4 may be divided differently and represent cognitive and affective correlates of EEG activity native to processes of musical interaction. Methods of feature extraction from such EEG representations for BCMI application will be described in the following section.

EEG Feature Extraction and Classification

There are various methods for transforming the raw EEG data, and analyzing it to identify features for use in the musical engine stage of a BCMI described in Figure 1. Algorithms are used to automatically isolate a set of relevant features, a set of relevant channels, or features from specific channels based on their location on the scalp (Lotte 2014). In other words, specific brainwave activities selected to control a BCMI are tracked over time and are assigned as control inputs.

The mathematic algorithms which describe the conversion of electrical brainwaves into a spectrum of sinusoidal waveforms and simultaneously identifying meaningful features for elicitation of control and indeed the computation power required to actuate these algorithms in real-time for BCI applications originate from methods for analyzing EEG data for research or clinical diagnosis. For reasons mentioned in the introduction of this paper, BCMI research has mostly been limited to using algorithms from the field of BCI. The most common function of these algorithms is pattern or feature recognition, and thus the classification of processed EEG data (Lotte et al. 2007). In other words, these classification algorithms look for patterns or features in the EEG signal specific to a mental command or emotional state and relay parametrical information to be mapped by the musical engine in a BCMI system (see Figure 1).

Classifier algorithms are chosen for the EEG features and properties they describe and must overcome the fact that EEG signals contain a lot of noise and have a high dimensionality (Rakotomamonjy et al. 2005). Noise is filtered by identifying and subtracting it from the signal, but with regards to high dimensionality, consider that in some contexts algorithms are used to extract multiple features from various channels across several segments of time (Haselsteiner, Pfurtscheller 2000). Although many BCI applications have achieved their aims using only one classification algorithm, some have used multiple algorithms aggregated in different combinations to concatenate a single feature or group of features (Lee, Choi 2003; Lotte et al. 2007).

Two main types of EEG data are typically used for feature extraction for BCMI applications: event-related potentials (ERPs) and the spontaneous EEG. ERPs are events observed as changes in the EEG spectrum due to external events or stimuli. Systems using spontaneous EEG data analyze the ongoing data stream for trends or patterns that match specific neural activity. One of the first and most commonly used transformations of the spontaneous EEG in early BCMI systems is a fast Fourier transform (FFT), which averages the amplitude of specific frequency bands over time (Miranda 2006a, 2006b; Nunez and Srinivasan 2006; Tan, Nijholt 2010; see Figure 4). Using the FFT algorithmic transformation, frequency bands that have higher amplitudes averaged over a specific period of time are considered to reflect attributes of the dominant mental state for that period (Teplan 2002; Zhuang et al. 2009). The divisions or thresholds of the frequency spectrum vary slightly between different studies according to the type of activity in focus. This type of transformation has been useful in BCIs aimed at actuating output responding to metrics such as alertness and relaxation, and has been instrumental in developing neurofeedback techniques where, for example, listening to the sonification of the transformed signal allows the user to learn to consciously steer the EEG towards desired mental states (Tan, Nijholt 2010; McCreadie et al. 2013). In other words, a user may learn to manipulate the amplitudes of individual frequency bands by undergoing neurofeedback training, thereby learning to control a BCMI system designed to map those parameters to output designated audio/visual content or events. Other types of algorithms can track spectral dynamics, extracting information about changes or peak amplitudes within a specific frequency band to be used as features for sonification or control (Hinterberger 2011; Wu et al. 2010). Thus, the FFT has been an attractive and reliable candidate for feature extraction in relatively simple BCMI systems of the EEG sonification type (see Table 1), where in such a case a user's overall mental state sonified in this way could be used to control associated musical dynamics or tempo.

In practice, neurofeedback training for a BCMI application aimed at optimizing affective performance may be divided into slow wave and fast wave training. The goal of slow-wave alpha/theta (A/T) training could be for the user to raise the amplitude of slow waves Theta range (4–8 Hz) above that of the Alpha range (8–12 Hz), while in fast-wave training the goal may be to raise the amplitude of sensor-motoric rhythms (SMR) in the low beta range (12–15 Hz) and maintain it without allowing frequencies higher or lower in the spectrum to rise concurrently. This type of training has shown to improve musical performance on several standardized evaluation scales proposed for judging the quality of a musical performance such as level of technical security, musicality, expressive range and communication of emotional commitment and conviction to name a few (Gruzelier 2011). Because of these benefits, as well as the fact that one learns to modulate amplitudes between specific frequency bands, this type of training could be a prime candidate for learning to control a BCMI system. But modulations within specific EEG spectrum frequency bands are only one type of feature which may be extracted for BCMI system control.

More advanced BCMI systems of the EEG musification and BCI control types (see Table 1) rely on other features of the EEG signal which are event related (they look for ERPs). For example, imagining body movement, gazing at a blinking light, recognizing a picture, or doing mental tasks produce features in the EEG signal that can be used to command a BCI (Miranda, Castet 2014). These have been explored at various depths in the literature, but in a recent (2014) introductory chapter to EEG-based BCIs, author Ramaswamy Palaniappan identifies several BCI paradigms of feature extraction charted onto Table 3 (Palaniappan 2014).

Table 3. BCI paradigms of feature extraction (adapted from Palaniappan, in Miranda, Castet 2014: 34–37)

BCI Paradigm	**Description**	**Feature Details**	**EEG Analysis**	**BCMI Application Example**
Motor imagery	• Imagining simple body movement, such as hand movement, produces changes in the EEG called event-related desynchronization (ERD) and event related synchronization (ERS). • Example: Imagining moving the left hand results in an ERD in the right motor cortex, and an ERS in the left motor cortex.	• Frequency range: 8–30 Hz (alpha and beta bands). • 10–20 electrode location: C3, C4. • EEG feature: simultaneous ERD and ERS. • ERD: EEG attenuation in primary and secondary motor cortices. • ERS: EEG amplification in the ipsilateral hemisphere.	• Identifying relevant electrode locations. • Determining spectral range. • Choosing features for detecting the type of motor imagery.	• Imagined movement is represented by sonic events.
Steady-state visual evoked potential (SSVEP)	• Gazing at visual stimulus that flashes or blinks at 6 Hz and above entrains the EEG in the visual cortex to that frequency. • Example: Focusing on a blinking LED light or target area on a screen results in the same frequency appearing in the occipital region of the visual cortex.	• Frequency range: 6–60 Hz. • 10–20 electrode location: O1, O2. • EEG feature: spontaneous frequency following effect of the brain.	• Detecting and isolating the target feature.	• Choosing a specific flashing visual stimuli to focus on indicates a command for the music engine (see Figure 1) to carry out.

P300 Visual evoked potential (VEP)	• EEG feature occurring 300–600 milliseconds after exposure to visual stimuli. These can be letters or numbers arranged in a grid of flashing rows and columns. • Example: Task-relevant or decision-making stimuli such as recognizing a picture or choosing a number from a flashing grid results in a P300 response in the parietal cortex.	• Frequency range: 8 Hz and below. • 10–20 electrode location: Fz, Cz, Pz. • EEG feature: higher P300 amplitude will occur for the object in the visual stimuli focused on.	• Involves multiple trials due to higher background EEG.	• Choosing musical notes from a flashing grid for composing a melody. • Choosing from a number of musical parameters to control in the musical output.
Mental task	• Specific types of mental task activate specific brain regions and can be detected as inter-hemispheric patterns in the EEG. • Example: Doing math equations in the mind results in higher EEG activity in the left hemisphere than the right hemisphere.	• Frequency range: 8–30 Hz. • 10–20 electrode location: all channels in two groups – left and right hemisphere locations. • EEG feature: distinct differences in EEG activity between brain hemispheres.	• Uses an asymmetry ratio to compare EEG amplitude between hemispheres.	• Tasks such as improvisation and score reading result in different patterns of activity between brain hemispheres. • The type of mental effort a user is engaged in affects the sound of a musical instrument being played.
Slow cortical potential (SCP)	• Changes in the low frequency range of the EEG are associated with certain tasks. • Example: Planning or preparing to move causes a dip in amplitude in the low frequency range of the EEG.	• Frequency range: 1–2 Hz. • 10–20 electrode location: dependent on targeted task. • EEG feature: modulation between positive and negative power SCP.	• Relies on extensive user conditioning to learn to manipulate the SCP.	• Manipulating the SCP allows a user to modulate between distinct musical timbres.

All of these paradigms identify useful features for mapping to musical parameters or commands but each have strengths and weaknesses for application in BCMI systems. Motor imagery tasks currently only cause changes in the EEG after a few seconds latency and requires user training, but does not require visual stimuli to work (step 1 of Figure 1). Mental tasks also do not require visual stimuli, but this method relies on frequent use and re-training as patterns representing specific tasks change over time. The disadvantage of SSVEP and P300 VEP methods is that focusing on flashing visual stimuli is practical for only a few minutes at a time and runs the risk of triggering epileptic episodes, however the major advantage is that they require as few as one electrode to work. The SCP method requires extensive conditioning to learn to control, but is very reliable in terms of performance (Palaniappan 2014). Therefore, any venture into the BCMI research and application space today must make an informed choice of mapping methods depending on its ultimate purpose.

The next step in the BCMI system involves mapping these features to control parameters relevant to studying or supporting a specific musical activity. The following section discusses the role of mapping and describes some of the prevalent strategies that have been reported in the literature.

Following feature extraction, mapping the isolated and transformed EEG information to music in the musical engine (see Figure 1) is the next step in a BCMI system. Much BCMI research has given focus to mapping because of its analogies to the complex interaction between musicians and their instruments, and because it gives rise to degrees of control through which levels of expressivity and intention can be conveyed (Miranda, Eaton 2014). The role of mapping in BCMIs is akin to becoming accustomed to playing a musical instrument in the sense that the features extracted from the EEG (such as the amplitude of beta band waves measured between hemispheres) can become the 'fingers' of a user upon a virtual instrument, or plot a cross-fade between two types of music stored in the system based on the user's object of focus, just to name two hypothetical examples. Mapping in digital or electronic-based musical instruments has been defined as the correspondence between control parameters derived from user actions and sound synthesis parameters, and can be further classified in terms of the complexity of its signal relationship (the number of connections existing between input and output parameters; Hunt et al. 2000; Miranda, Eaton 2014). Table 4 describes four types of mapping strategies.

Table 4. Types of mapping strategy based on signal relationship complexity (adapted from Hunt et al. 2000: 210)

Signal Relationship	**Description**	**BCMI Application Example**
One to one	A single input parameter is mapped to a single output parameter.	A P300 VEP response triggers playback of a single musical pitch.
One to many	A single input parameter is mapped to multiple output parameters.	Average amplitude of the alpha frequency band modulates attack velocity, timbre and reverb of a synthesizer instrument.
Many to many	A number of input parameters are mapped to a number of output parameters.	Each band of the EEG frequency spectrum is assigned control over activating different musical instrument sounds, as well as their placement in a stereo field.
Many to one	Multiple input parameters are mapped to a single output parameter.	Motor imagery of a hand gesture (ERD, ERS) while focusing gaze on visual stimuli (SSVEP) results in the playback of a stored musical fragment.

Mapping strategies can therefore greatly determine the level of interactivity a user may experience using a BCMI, and choices made in reports in the literature are usually based on the goals of the system's design, but sometimes limited by cost or technology.

One clear distinction between playing an acoustic instrument and playing a BCMI, is that in acoustic instruments mapping is explicit – plucking a string directly results in a musical tone; in BCMIs, mapping uses generative mechanisms – neuronal activity. The lack of apparent cause and effect relationships between the user's actions and the output from the musical engine is often the source of criticism for BCMIs with passive or selective types of control.

As aforementioned, all BCMI systems are unique, though certain hardware and software components appear more often in the literature. However, BCMI systems can be classified by the type of control achieved as a result of their designs (Hunt et al. 2000; Miranda, Eaton 2014; Wadeson et al. 2015; Eaton, Miranda 2016). Table 5 describes four major types of control that have been achieved in BCMI documentation.

Table 5. Types of control in BCMI systems

Type of Control	**Description**
Passive	Returns stored media in the form of musical sounds, fragments or textures as output. Does not rely on intentional commands from the user.
Selective	The user learns to steer his or her EEG, in effect, learning to cognitively adjust levels of attention, arousal or emotion in order to intentionally manipulate the output of stored media.
Direct	Users interacts with software application which enables specific choices of output such as musical pitches or rhythms. These are often represented as tools or elements to choose from.
Collaborative	Enables more than one user to interact musically within the system. Some collaborative systems use passive or selective types of control.

From these types of control, we can observe their direct associations with the 3 main types of BCMI system described in Table 1: passive control is normally found in EEG sonification systems, selective control – in EEG musification systems, and direct control – in BCI systems. Collaborative control types can be possible in all 3 main types of BCMI system. Considering the wide variety of one-of-a-kind mapping strategies and disparaging technologies employed in literature reportage, the remainder of this section will focus on illustrating general principles with a few key examples. Many other examples of specific cases can be found compiled in books, and papers referenced within this review (Tan, Nijholt 2010; Gürkök, Nijholt 2013; Miranda, Castet 2014; Christopher et al. 2014; Wadeson et al. 2015).

A simple example of the EEG sonification type of BCMI could be what is widely considered to be the very first performance of a BCMI –

Music for Solo Performer by Alvin Lucier in 1965 (Gürkök, Nijholt 2013; Christopher et al. 2014). He amplified his EEG in the alpha range (in his case 8–13 Hz) from two electrodes attached to his forehead. This amplified signal was sent directly to a number of speakers, each of which was connected to an array of percussion instruments. The amplitude was controlled manually, and speaker channels were mixed individually, but another feature of Lucier's work was the triggering of recorded loops of alpha band activity that was transposed into the audible hearing range. These were triggered to play in response to the amplitude of the alpha rhythm exceeding a certain threshold (Miranda, Eaton 2014). This early BCMI could be described as having a one to many signal relationship, since his alpha waves were used to activate multiple speakers as well as trigger playback of a tape loop. It also could be considered as having a 'passive to loose' form of selective control, since he could to some degree influence the output by steering his EEG within the alpha range. As a conceptual composition piece, the image of the composer with his head fitted with wires, sitting motionless upon a darkened stage amongst an array of roaring percussion instruments responding to his brain, is validation enough for this type of BCMI. It's remarkable to note that this performance predates Vidal's first conceptualized BCI in 1973 (Vidal 1973; Tan, Nijholt 2010; Miranda, Castet 2014), a fact illustrating that progress in BCMI and BCI spur each other on.

Jumping ahead roughly 3 decades, a prime example of the EEG musification type of BCMI could be the BCMI piano created by Miranda and colleagues described in a paper called *Brain-Computer Interface for Composition and Performance* published in 2006 (Miranda 2006a). Here the system loads the sets of musical building blocks consisting of melodic fragments in two distinctly different compositional styles for piano (Robert Schumann and Ludwig van Beethoven) based on generative rules driven by data resulting from a Hjorth analysis[2] of 14 of electrodes (7 pairs to form a bipolar montage). A Hjorth analysis is a form of clinical EEG analysis which measures attributes such as activity, mobility and complexity in the spontaneous EEG (Hjorth 1970). Another data stream collects information about the signal's complexity and is mapped to the tempo and dynamics of the musical output. Mapping between the extracted EEG information in the first data stream and the types of musical style making up the musical building blocks were arbitrary. This BCMI design could be classified as having a many to many signal relationship since two individually transformed data streams are used as input, each of which manipulate more than one parameter. However, it also falls in the crack between passive and selective BCMI control types, as the musical building blocks are assigned arbitrarily and are triggered unconscious of user intent but the tempo and dynamics could be intentionally steered with neurofeedback training. The BCMI

[2] Named after Bo Hjorth.

piano is more of an early experimental prototype which demonstrated important proof-of-concepts within the emerging field than an instrument effectively capable of composition and performance.

As a final example, a multi-modal BCMI involving a table top interface will suffice. This system is described in a 2011 paper by Aleksander Väljamäe and colleagues entitled *Listening to Your Brain: Implicit Interaction in Collaborative Music Performances* (Väljamäe et al. 2011). Here the EEG is used together with hand-manipulated devices they call *Physiopucks* designed to react to their position and movement across a musical table top interface called *Reactable*. The EEG component used 4 channels for two participants, with one electrode placed on each of their upper foreheads (location Fz), and one electrode measuring heart rate from the wrist. The signal from the forehead was directly mapped in the range of 4–12 Hz (theta to alpha band), transposed into the audible frequency spectrum and streamed to the reactable tabletop interface, which detects the movement of 4 physiopucks placed upon it. The signal from the wrist (heart rate) generated the tempo. The signal from both the forehead and the wrist of one user are mapped to two individual physiopucks, while the other two remain unconnected to physiological signals but could be assigned control over other musical parameters such as audio filters or generators. This BCMI was designed for an experiment where pairs of participants were tasked with reproducing a fragment of music played to them by manipulating the physiopucks and the EEG collaboratively. The experiment aimed at measuring attributes of difficulty and distribution of control in learning to use a multimodal BCMI system. This example features a many to many signal relationship, as input sourced from both biosignals as well as physical movement physiopucks on the reactable table top results in output representing both physical and mental activity, embodied in the context of goal-oriented collaborative musical interaction. This experiment is an example of a collaborative type of control combining both, selective and BCI, elements – users need to learn to manipulate the physiopucks to replicate the reference music, therefore each trial is an attempt at discerning how manipulation of physiological signals, and physical movement of the physiopucks are related to the resulting sound. As higher degrees of control are obtained through trial and error, higher levels of efficacy can be observed in the collaborative musical interaction. Such cross-modal or solutions involving hybrid control is an important step towards future BCMI design, which may rely on the EEG for more of a supporting role for more explicitly mapped controls.

As a summary for this section, approaches to BCMI have been described and discussed from the EEG input stage to the musical engine stage shown in Figure 1. These approaches are not exhaustive, and references to newly developed techniques do appear in literature but have yet to be adopted for wider use (Miranda, Castet 2014). Time will tell which approaches will emerge as dominant in this new and rapidly developing field.

Prospects for BCMI Research

In conclusion, the source of the EEG signal is rich with information reflecting brainwave activity that can be analyzed to reveal mental processes, commands, states, as well as levels of arousal, attention and emotion (Leslie, Mullen 2011; Maskeliunas et al. 2016). Within the context of musical group behavior, these dimensions can be conveniently observed. In other words, the act of playing music together provides a framework within which dimensions of the EEG can be understood. Insofar as musical group behavior has been considered a microcosm of human social interaction, BCMI provides a novel way of observing and understanding human behavior (Keller et al. 2014), as well as a highly creative playing field for developing better BCIs in general.

Though the field of BCMI is in its infancy, the future looks bright for its application on both the technical and artistic front. For example, BCMIs are not yet capable of outputting imagined music – the elusive dream of music heard in the mind manifested instantly through speakers is not yet on the horizon, but it may be coming closer (Miranda, Eaton 2014). The field is still very new but growing rapidly, and some recent authors aim to reduce fragmentation by encouraging collaboration between research communities of different specializations, and by systematically comparing methods so that best practices can emerge (Miranda, Eaton 2014). Others encourage testing BCMI systems in more embodied contexts, focusing on the entrainment effect of music and how it affects people and musical interaction within newly created psycho-physiological situations that can be experienced outside of the laboratory (Lavy 2001; Clayton et al. 2005; McGuiness, Overy 2011; Volpe et al. 2016). At the present time, new improved hardware and software which hold great promise for more reliable, customizable, and portable BCMI solutions are becoming commercially available and used in peer-reviewed research papers (Levicán et al. 2017). In short, BCMI is fertile ground for the formation of creative ideas and new paradigms at the intersection of music, neuroscience and biomedical engineering.

List of Abbreviations Used in the Article

BCI – brain-computer interfacing

BCMI – brain-computer music interfacing

Cz – central site, on the top of the head (named after the cortical area where the electrodes are located)

EEG – electroencephalogram

ERD – event-related desynchronization

ERP – event-related potentials
ERS – event-related synchronization

Fz – frontal site, on the top of the head (named after the cortical area where the electrodes are located)

FFT – fast Fourier transform

fMR – functional magnetic resonance

Hz – hertz

MEG – magnetoencephalography

MIDI – musical instrument digital interface

O – occipital site (named after the cortical area where the electrodes are located)

Pz – parietal site, on the top of the head (named after the cortical area where the electrodes are located)

SCP – slow cortical potential

SSVEP – steady-state visual evoked potential

VEP – visual evoked potential

SMADZEŅU-DATORA SASKARNE: LAIKMETĪGĀS PIEEJAS UN PERSPEKTĪVAS

Džekins Pousons

Kopsavilkums

Atslēgvārdi: smadzeņu-datora saskarne mūzikas jomā (BCMI), elektroencefalogramma (EEG), mūzikas atskaņojums, muzikālā mijiedarbe

Mūsdienās ir pieejamas daudzas jaunās tehnoloģijas, kas tuvākajā nākotnē būtiski iespaidos mūsu muzikālo mijiedarbi. Jau tagad vienas paaudzes – 50 gadu – laikā šīs mijiedarbes veidi ir radikāli mainījušies. Raksta uzmanības centrā ir pieejas un perspektīvas, ko paver smadzeņu-datora saskarne mūzikas jomā (angliski *brain-computer music interfacing*; turpmāk saīsināti BCMI), un tiek sniegts pārskats par BCMI datortehnikas un programmatūras komponentiem, sonifikācijas un muzifikācijas tehnikām, elektroencefalogrammas (EEG) iezīmju paradigmām, kartēšanas stratēģijām un kontroles tipiem. Mūsdienās datortehnikas un programmatūras komponenti BCMI sistēmām ir lietošanai droši, pielāgojami un portatīvi. Tādējādi BCMI ir lauks, kas strauji atklāj arvien jaunas iespējas un muzikoloģiskās izpētes perspektīvas.

Elektroencefalogrammas tehnoloģija ir ļāvusi ielūkoties smadzeņu norisēs. To raidītie elektriskie impulsi, kas tiek pierakstīti, ir bagātīgi piesātināti ar informāciju par psihes procesiem, stāvokļiem un emocijām. Šos mērījumus ir ērti izmantot, analizējot smadzeņu-datora saskarni.

BCMI transformē elektriskos signālus mūzikas parametros un uz šī pamata producē mūziku. Līdz ar to EEG tiek *muzificēta*; pievēršanās šai jomai ļauj pētniekiem labāk izprast smadzeņu darbības procesus un veiksmīgāk attīstīt smadzeņu-datora saskarnes ideju (*brain-computer interfacing*; saīsināti BCI) kopumā. Respektīvi, BCMI ir gandrīz tas pats, kas BCI, taču piemērots ar mūziku saistītiem mērķiem.

BCMI iespēju lauks ir vēl gandrīz neapgūts, taču tas strauji aug; lai novērstu sadrumstalotību, dažādu specializāciju pētniekiem būtu vērts apvienoties un sadarboties; metodes būtu pastāvīgi jāsalīdzina, līdz tiek atrasta vislabākā pieeja. Ir svarīgi testēt BCMI sistēmas dažādos kontekstos, novērojot, kā jaunie muzikālās saskarnes tipi (reālajā pasaulē, ārpus laboratorijas) iespaido izturēšanos un atskaņojumu. Mūzikas pētījumi tādējādi sniedz labu iespēju atklāt noteiktus muzikālās saskarnes aspektus saiknē ar smadzeņu viļņiem. Piemēram, svarīgi ir analizēt, kā smadzeņu viļņu ritmi muzikālās darbības laikā var sinhronizēties un kā tas atspoguļo mūsu mūzikas pieredzi. Sinhronizēta fiziskā un emocionālā atsauksme uz mūziku ir visai izplatīta ekoloģiski validos kontekstos. Šī fenomena izpēte neironu korelācijas aspektā

varētu atklāt tiešākus kanālus uz kāda indivīda smadzeņu viļņiem, kas savukārt spēj iespaidot cita indivīda smadzeņu viļņus.

Neirofīdbeka pētījumu rezultāti tiek izmantoti terapijā, lai atbilstoši tai vai citai iecerei sasniegtu noteiktu psihes stāvokli. BCMI sistēmu iespējams integrēt šīs atgriezeniskās saites apmācības protokolā, proti, apmācīt interesentus, lai viņi spētu radīt vai kontrolēt mūzikas produktu saskaņā ar prāta diktētajiem mērķiem; to vidū var būt, piemēram, uzmanības koncentrācija vai nomierināšana. Ļoti vienkārši piemēri ir Alvina Lusjē pirmās EEG vadītās kompozīcijas: viņš vēlējās, lai viņa smadzeņu viļņi noteiktos brīžos ģenerētu alfa viļņu aktivitātes uzliesmojumus.

BCMI sistēmas ir visai noderīgas, arī pētot t. s. ķermenisko muzikālo mijiedarbi (*Embodied Musical Interaction*). Tās ietvaros koordinēti norit liels daudzums mentālu procesu, un to aspektus var izmantot arī, lai celtu darba ražīgumu vai veidotu efektīvāku komunikāciju. Piemēram, mūziķi bieži sarunvalodā piemin atrašanos "grūvā" (*in the groove*), kad izjūt augstu savstarpējās koordinācijas līmeni. EEG var palīdzēt mums izprast, kā atrašanās "grūvā" atspoguļojas smadzeņu darbībā, un BCMI spēj iemācīt mums sasniegt šo stāvokli ātrāk.

Šobrīd BCMI izpētes laukā iezīmējas vairāki pamatuzdevumi. Pirmkārt, ir sarežģīti noteikt un iegūt aprīkojumu, kas nepieciešams šāda veida pētniecībai. Otrkārt, it īpaši medicīnas un mūzikas pētījumos ir nepieciešamas zināšanas datorprogrammēšanā, lai būtu iespēja izmantot algoritmus, kas tiek lietoti, klasificējot un interpretējot EEG datus; tie ļauj iekļūt BCMI sistēmā, kas jau rada pamatu smalkākiem un efektīvākiem kontroles mehānismiem. Treškārt, šo datu transformācija mūzikā prasa zināšanas par datorkomponēšanu, īpaši par programmatūras aspektu, jo jāsaņem ievērojams datu daudzums un tas jātransformē mūzikas parametros. Ceturtkārt, ekoloģiski validu eksperimentu izstrāde var sagādāt nopietnas problēmas BCMI sistēmām; to nosaka gan EEG ierīču mazā pieejamība, gan tas, ka šo ierīču izmantojuma laikā grūti ir panākt ķermeņa kustību brīvību – EEG pieraksts ir ļoti delikāts un jūtīgs process, jo spriedze, ko varam nolasīt no skalpa mērījumiem, ir ļoti vāja.

Rezumējot jāsecina, ka EEG signāls ir bagātīgs informācijas avots, taču mums jāmācās to interpretēt un izmantot gan praktiskiem, gan mākslinieciskiem mērķiem. BCMI pētniecība ir jauna joma, bet tā strauji attīstās, un to sekmē arvien modernāku tehnoloģiju pieejamība, kā arī uzkrātā pieredze. Ir liels potenciāls muzikālās mijiedarbes un tās atstātās ietekmes analīzei, fiksējot psihes procesus ar EEG muzifikācijas palīdzību. Mums jāatrod radoši veidi, kā jaunās tehnoloģijas izmantot pētniecībā, lai labāk izprastu sarežģīto psihofizioloģisko pieredzi, kādu ietver muzikālā mijiedarbe, un lai izmantotu tās sniegtās priekšrocības kompozīcijas procesā, mūzikas terapijā un apmācībā.

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