

MAKING MUSIC WITH BRAINWAVES: BRIDGING SYSTEMATIC MUSICOLOGY AND NEUROSCIENCE WITH BRAIN-COMPUTER MUSIC INTERFACE RESEARCH

Jachin Edward Pousson, Valdis Bernhofs



This article explores the integration of systematic musicology and neuroscience through Brain–Computer Music Interfaces (BCMI), highlighting its potential to reshape how musical interaction is understood and practiced. Building on traditions from Helmholtz and Adler to contemporary neuromusicology, the study situates EEG-based research within a “third wave” of music–brain studies that emphasizes ecological validity, expressive intent, and inter-brain synchrony. At Jāzeps Vītols Latvian Academy of Music (JVLMA), EEG studies of expressive piano performance and hyperscanning during musical interaction provide novel insights into intra- and inter-brain dynamics. These findings are applied to the design of BCMI systems that function as genuine musical instruments rather than laboratory artifacts, enabling musicians to shape sound and visual environments through neural states in real time. Artistic applications, including orchestral works and electronic performance systems, demonstrate the feasibility of BCMI as both a scientific tool and an artistic medium. Beyond technical innovation, the research underscores institutional benefits: developing in-house EEG capacity strengthens interdisciplinary collaboration, attracts international partnerships, and positions music institutions at the forefront of an expanding field. The article argues that BCMI represents not only a frontier for science and art, but also a model for institutional growth and interdisciplinary research in music and neuroscience.

181

Keywords: EEG, BCMI, Systematic Musicology, Neuroscience

INTRODUCTION

Musicology in its broadest sense encompasses systematic, historical, and ethnographic approaches to understanding musical life. Each of these domains is concerned, albeit in different ways, with how musical meaning is created, transmitted, and experienced. Neuroscience adds yet another perspective: it provides empirical access to the brain and body processes that unfold during musical activity.

The integration of neuroscience into systematic musicology is relatively recent. Hermann von Helmholtz laid the physiological and acoustical foundations for what later became systematic musicology (Helmholtz 1877), while Guido Adler offered the first explicit definition of *Musikwissenschaft* as comprising historical and systematic branches (Adler 1885). Although the foundations of systematic musicology were laid in the 19th century, the direct application of neuroimaging and other brain-based methods to the study of music emerged much later. It was only in the late 1980s and 1990s that techniques such as electroencephalography (EEG) and other neuroimaging methods, including positron emission tomography (PET) and functional magnetic

resonance imaging (fMRI) began to be systematically employed in music research (Zatorre 2001, Peretz and Zatorre 2005). By the early 2000s, neuromusicology had consolidated as a recognized subfield, with institutions such as the Max Planck Institute for Human Cognitive and Brain Sciences in Leipzig (Koelsch 2005), McGill University in Montreal (Robert J. Zatorre, Isabelle Peretz), and Finnish/Scandinavian networks (Mari Tervaniemi, Risto Näätänen) leading the way.

Since then, systematic musicology and neuroscience have increasingly overlapped through paradigms such as embodied music cognition (Leman 2008), hyperscanning for studying social interaction (Lindenberger et al. 2009, Sängler et al. 2013), and the development of brain–computer music interfaces (Miranda & Castet 2014). Globally, the field can now be described as entering a “third wave”: moving beyond proof-of-concept studies toward ecologically valid, socially embedded contexts such as group improvisation, live performance, and music therapy.

In Latvia, systematic musicology has developed rapidly, though it remains a relatively young discipline. The integration of neuroscience into Latvian music research began with early collaborations with the Department of Neuroradiology at Heidelberg University (Peter Schneider), where musicality assessment tools were developed for use in clinical research. At Jāzeps Vītols Latvian Academy of Music (JVLMA), the first in-house EEG-based music studies were launched in 2019 in cooperation with Vilnius University (Biophysics Department, Lithuania) and National Sun Yat-sen University (Neuroergonomics Lab, Taiwan). This initiative positioned JVLMA among the very few European music institutions with its own EEG capability. Since then, the EEG laboratory has enabled Latvia to participate in cutting-edge international projects, including investigations of expressive intent in piano performance (Pousson et al. 2021), EEG connectivity during music performance (Ghodousi et al. 2022, 2023), and inter-brain synchronization during musical interaction (ongoing since 2022).

The JVLMA team’s research stands out for integrating systematic musicology, artistic practice, and neuroscience from the very beginning, rather than adopting neuroscientific methods only at a later stage. At JVLMA, one of the main research directions focuses on Brain–Computer Music Interfaces (BCMI) and ecologically valid performance settings, which together give Latvian research a distinctive profile in this emerging international field.

The novel contributions of the Latvian team include a clear prioritization of ecologically valid performance settings over passive listening paradigms, the incorporation of expressive intent and inter-brain synchrony into BCMI design rather than relying solely on emotion detection, and the demonstration of concrete artistic applications that extend usability beyond the laboratory.

This article reflects on the development of this approach and its implications for systematic musicology and Brain–Computer Music Interface (BCMI) research. It provides an overview of systematic musicology research employing neuroscience

methodology at JVLMA since 2019. The overarching research goal has been to design BCMI systems as new kinds of musical instruments, enabling novel forms of musical communication and expressivity.

This article is written primarily for Systematic Musicology readers, and aims to provide a focused perspective on the implications of using neuroscience methodology to investigate musical phenomena. As such, some technical details necessary for neuroscience readers are not included here, but can be found in the previous articles published by our research team (Pousson et al. 2021, Ghodousi et al. 2022, Ghodousi et al. 2023, Pousson et al. 2023).

For Systematic Musicologists, a brief narrative of how our music institution became capable of recording EEG data is included, because it bears good examples of how inherent inter-disciplinary challenges were overcome. For ease of understanding, a brief explanation of key terms is provided below:

Electroencephalography (EEG): A neuroimaging technique which measures differences in electrical potential typically in the 0.5-100 microvolt (μV) range between locations across the scalp and a reference site (Berger 1929, Teplan 2002).

Embodied Music Interaction (EMI): A Systematic Musicology research paradigm holding that body movement is central to music cognition.

Brain-Computer Interface (BCI): A system combining EEG hardware and real-time analysis software, enabling a user to control a computer using their brain signals.

Brain-Computer Music Interface (BCMI): A BCI designed for musical purposes – for research, education, training or performance.

Hyperscanning (HS): A method of recording synchronized EEG signals from two or more brains simultaneously, in order to study human interaction.

Inter-Brain Synchronization (IBS): Synchronization in the EEG signal between two or more brains, which may be measured using various approaches.

These terms come together in our research work in the following way: The **EEG** method is used to record the brain activity of musicians engaged in **EMI**. This EEG data is then analyzed for evidence of **IBS** and characteristics which could be potentially classified in real-time for **BCI** applications. The **HS** method provides the prospect of **IBS**-based collaborative **BCMI** systems in the future.

This research is beneficial for both systematic musicology and neuroscience by connecting two important steps. First, to increase a fundamental understanding of neurophysiological processes underlying EMI – a complexly coordinated yet under-investigated human behavior. Second, to harness this increased understanding to develop BCMI tools that enable musical growth and potentially benefit human communication, cooperation and coordination.

BACKGROUND: THE BCMI FIELD AS AN INTERDISCIPLINARY BRIDGE

Systematic Musicology is an umbrella under which neuroscience, music computing, and embodied music interaction research co-exist – and the field of Brain-Computer Music Interfacing is in an excellent position to help bridge them. It has been the duty of our research efforts to take careful consideration of research paradigms inherent to the overlapping disciplines and to respectfully and creatively find appropriate solutions for working together.

Musicologist Marc Leman reflected on systematic musicology's role in scientific investigation of musical phenomena, and called for more direct multi-disciplinary collaboration between the musical arts and the sciences. He explained that embodied music cognition involves a dynamic loop of energy transfer from bioelectrical processes in the brain to biophysical energy output from the human body, into a musical instrument which converts this into acoustic energy, completing the loop upon re-entering the brain through the ears of the performers and listeners (Leman 2008, 104). In Leman's view, all parts of this dynamic loop are essential to the experience of performing music, and so removing any of them to isolate some part of the process in favor of experimental control undermines the ecological validity of the findings (Leman and Maes 2014, 236–237; Leman et al. 2017, 1). For example, the brain of a pianist lying down in an MRI scanner is certainly in a different state than if they were on the concert stage. What conclusions could then be reliably drawn from data collected in unrealistic situations? Leman encouraged a multi-disciplinary approach which could accept mixed methods to bridge these gaps. We often hear this advice of Leman's ringing true on our research path.

Our systematic musicology laboratory at JVLMA obtained our first clinical grade EEG device – an Enobio 32¹ in 2019 through a two-year collaborative project (LV-LT-TW Scientific Cooperation) together with neuroscientists from the Biophysics department at Vilnius University in Lithuania and the Neuroergonomics department at National Sun Yat-sen University in Taiwan. The project's goal was to develop a BCMI system for embodied music interaction – which clearly necessitated the alignment of musicological and neuroscientific goals. The neuroscientists recommended to begin with collecting EEG data from piano playing subjects. They would then report characteristics in the power spectrum and discuss how these may support processes underlying expressive music performance. The systematic musicology team members would then be able to use this outcome to develop BCMI software to detect different expressive states in real time. We needed to coordinate closely to plan steps to achieve these aims and overcome challenges which have hindered BCMI research pursuits in the past. The following section is a reflection of our interdisciplinary team's experience in facing these challenges.

¹ <https://www.neuroelectrics.com/products/clinical/enobio-dx>

CHALLENGES OF MUSIC-NEUROSCIENCE RESEARCH

EEG music studies are currently scarce, and we soon discovered why. Three major challenges stand out currently. First, typical EEG studies require subjects to remain still so as not to introduce noise artifacts from body movements into the EEG signal, whereas typical music interaction requires body movement to play an instrument or to respond naturally. Second, there are only a few music institutions in the world with access to equipment and expertise in both musicology and neuroscience fields. Third, there are semantic gaps between how we speak about music – in terms of physical/architectural properties or in terms of perceptual/experiential properties. Overcoming these sometimes involved the painstaking explanation of fundamental concepts between the neuroscientists and musicologists, but respectful communication allowed for meaningful discussions and deeper understanding.

Regarding the first challenge, it is important to acknowledge that the EEG is currently a fragmented field of practice. Unfortunately, consumer EEG devices and the companies producing them have increasingly targeted the mental-wellbeing market with lofty claims, which has in turn obscured fundamental principles of the EEG method and its data analysis from public view. Before we were able to obtain the clinical grade EEG system we experimented with several consumer grade EEG headsets claiming BCI capability. Such devices were found unsuitable for either research or BCMI applications due to latency, unstable connections, or poorly developed proprietary software (Maskeliunas et al. 2016, 18–21). The clinical grade EEG system however, was able to record in a format and quality which the neuroscientists could accept working with. They formulated a preprocessing pipeline for our study to allow for and to filter out body movements necessary for playing the piano. In order to simulate the removal of body movement artifacts in real time at the stage of developing a BCMI system, signals from individual electrodes that were likely not originating from the brain (above 100 microvolts) were filtered out.

Regarding the second challenge – when our systematic musicology team visited our neuroscience project partners in Lithuania and Taiwan, we caught our first real glimpse into their world. Vilnius University has a reputable biophysics department and EEG lab, and National Sun Yat-sen University has a Neuroergonomics lab designing EEG hardware and building BCI game controllers. When we presented our goal to build a BCMI for EMI applications, the feedback from neuroscientists revealed that some of our assumptions about real-time EEG classification were quite naive. There are thousands of articles published about emotion detection in the EEG but currently only a handful have collected data from subjects during music performance. Furthermore, the concept of an emotion-driven BCMI was further confounded by the issue that actual felt emotions and aesthetically expressed emotions are often not the same during music performance. This distinction is rarely made in music research using the EEG method, so careful consideration was needed to guide our approach.

The neuroscientists recommended that to move towards our goal of building a BCMI system, we should begin by training to collect EEG data. Next, we would design an experiment, program a recording protocol, set up an EEG lab space at JVLMA, and record our own EEG dataset of musicians performing. Once that data set was analyzed and the results reported, we could then proceed to the next step of programming BCMI software based on those findings. After accepting this plan, we pressed forward to take the necessary first steps, gaining new skills and learning scientific standards for EEG data collection and analysis.

As for the third challenge – our research vocabulary increased as the neuroscientists on our team began to train the musicologists to collect data with our EEG device and evaluate our first EEG recordings for signal quality. We worked together to design an EEG data collection protocol that aimed to maintain maximal experimental control while accounting for human factors including the number of times a one-minute piano score could be repeated within a single recording session, the amount of rest time between recording sessions, and the configuration of the recording environment to avoid a hospital-like setting. Over the course of many discussions, mutual respect for each other’s disciplines grew. The neuroscientists began to appreciate the potential for music interaction as a framework for EEG research and took on the challenge with us to choose approaches that upheld the standards of both of our fields. Taking all points into consideration, we were able to modify a music practice room in the music academy to function adequately as an EEG recording room.

186

THE EEG METHOD AND IMPLICATIONS FOR MUSIC RESEARCH

Electroencephalography (EEG) is an often-used method for brain music studies, chosen for its high temporal resolution and mobility in ecologically valid environments compared to other neuroimaging techniques (Czeszumski et al. 2020, 3). Consider a few facts about the EEG method: a) The EEG signal itself consists of differences in electrical potential measured in the microvolt range between specific locations on the scalp and a reference site over time (Teplan 2002, 5), and these are recorded in software on a computer, b) An EEG recording protocol is a chosen or bespoke software that controls the sequence of the experiment, and marks EEG data at the precise onset and offset of events in the sequence for later analysis, c) EEG data needs to be preprocessed before analysis to filter noise, remove artifacts, and cut it into segments known as epochs. Furthermore, analysis typically involves superimposing as many epochs as possible upon each other to find evidence of the brain’s responses to specific stimuli or tasks. These facts had several implications for an experiment design involving musicians playing musical instruments summarized in the next paragraph.

Implications of the first fact were that the recording space needed to be away from the street and heavy electrical systems like elevators or kitchens as these might become unwanted sources of electrical line noise. The space also needed to be furnished to minimize electrical noise from computer equipment, lights and telecommunications.

It also needed to be arranged in such a way that participants could play a piano in a natural seated posture while wearing an electrode cap with a USB cable attached to the back of it for EEG signal acquisition. Another implication of working with signals in the microvolt range is that it takes approximately 30–45 minutes to place the electrode cap on a subject's head, apply conductive gel to all electrodes and make adjustments for a quality signal. The second fact implied that the sequence of the experiment needed to be programmed using third party software capable of communicating with our EEG recording software, defining the number of trials and their groupings into runs and sessions while taking into consideration a realistic number of trials that could be recorded per subject, per day. The third fact implied that analysis results may not be applicable to BCMI for live performance since this requires real-time EEG analysis. We needed to wait for the outcomes before we could find out if they were indeed useful for our intended purpose. In the following section, two research projects are described and outcomes discussed, in particular those with implications for BCMI applications.

EEG RESEARCH ON EMBODIED MUSIC INTERACTION: PRELIMINARY RESEARCH: CHARACTERIZING EXPRESSIVE INTENT IN THE EEG DURING PIANO PLAYING

Our first EEG research project aimed to investigate brain activity during expressive music performance. Expressive intent is a term describing how instrumentalists employ expressive cues to communicate musical intentions (Sloboda and Juslin 2010). These expressive cues may be written or only implied in a musical score but they serve to communicate certain moods or evoke certain emotional responses in context of the narrative of the piece (Juslin and Västfjäll 2008, 566), if there is one. For example, *legato* and *staccato* playing may serve to evoke contrasting emotions in a piece. On this basis we aimed to characterize brain activity related to the act of playing expressively with intent to communicate contrasting moods.

We adopted Russell's Circumplex model of affect (Russell 1980, 1164) as a basis for labelling five contrasting moods; Neutral, Distressed, Excited, Depressed and Relaxed as shown in Figure 1. The piano was chosen for its ubiquity in academic music discipline.

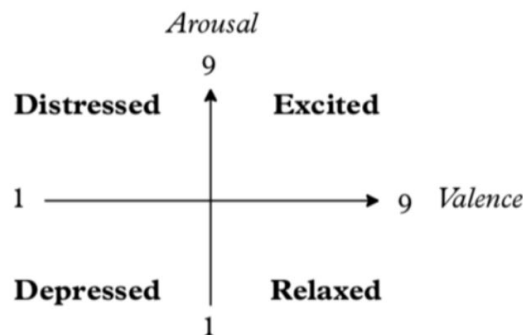


Figure 1: Two dimensional model of affect using 9-point scales on the dimensions of Arousal and Valence, based on the Circumplex model of affect (Russell 1980, 1164).

A music score with a duration of 60 seconds was composed for participants to play on the piano as shown in Figure 2. The score was designed so that it was easy to learn quickly and the music consisted of a melody with bass accompaniment in an extended pentatonic scale to avoid dominant-tonic tensions which could confound the task of playing the same score with different expressive intentions. The first 30 seconds were to be played Neutral, without expression at a strict tempo. The next 30 seconds were an exact repeat, to be played with intent to express one of the four other contrasting moods (Fig. 1). The note heads on the second page lacked rhythmic durations and included the option to repeat if time allows, providing a greater degree of freedom to interpret rhythmic phrasing, tempo, dynamic, articulation and embellishment appropriate for the intended expression.

Neutral ♩ = 120

Piano

mf

5

Pno.

9

Pno.

13

Pno.

Expressive ♩ = free

17

Pno.

Free dynamics, articulation, embellishment.

21

Pno.

25

Pno.

29

Pno.

Repeat if time allows, until timer ends.

Figure 2: Music score designed for the performance task in this study. The left page is performed without expression (Neutral) while the right page is a repeat, played expressively.

The neuroscientists determined that a dataset of 10 participants with 200 trials per participant was adequate for the scope of this project. We determined that with each trial consisting of a one-minute piano-playing task, participants could realistically complete a maximum of 50 trials in a single recording session; therefore four sessions per subject were scheduled on different days. Each session was divided into 10 runs consisting of five trials each. The sequence of a single trial is shown in Figure 3. The EEG recording protocol was programmed accordingly to mark onsets and endings of each trial per run and session. EEG data was recorded using a clinical grade 32 channel EEG system (Enobio32) at a sample rate of 500Hz. Please refer to the published article (Pousson et al. 2021, 3–5) for technical details and the analysis pipeline.

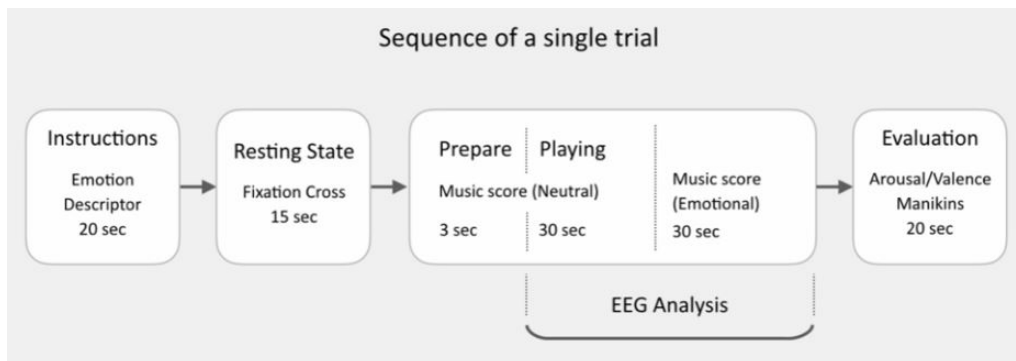


Figure 3: Sequence of a single trial of the EEG recording protocol used in this study. Subjects were guided through this sequence via instructions presented on a screen placed at eye level on top of an upright piano.

This experiment design enabled us to capture brain activity from musicians in five contrasting conditions during the act of expressive music performance. In order to connect findings to the wider neuroscience field, the biophysicists recommended a spectral power analysis across four Regions of Interest (ROI). They averaged together the spectral power data per condition from all 10 pianists, grouped the electrodes into ROIs at the front left, front right, back left and back right of the head, and plotted the results as shown in Figure 4.

Each of the four charts represents an ROI, and the plotted data shows the power spectrum per expressive condition relative to the Neutral condition averaged together from all 10 subjects over all 2000 trials. Here we were able to see small differences between contrasting conditions. In the High Arousal (HA) conditions Distressed and Excited, there were greater differences in the Delta-Theta range in the Left Frontal and Right Pareto-Occipital ROIs. There were also greater differences observed between the same conditions in the Gamma range, but between the Left and Right Frontal ROIs (see light orange boxes). As for Low Arousal (LA) conditions Depressed and Relaxed, nearly no differences could be seen relative to the Neutral condition, except in the Delta range in the Left and Right Parieto-Occipital ROIs. Finally, a suppression of the Alpha band could be seen across all conditions and ROIs.

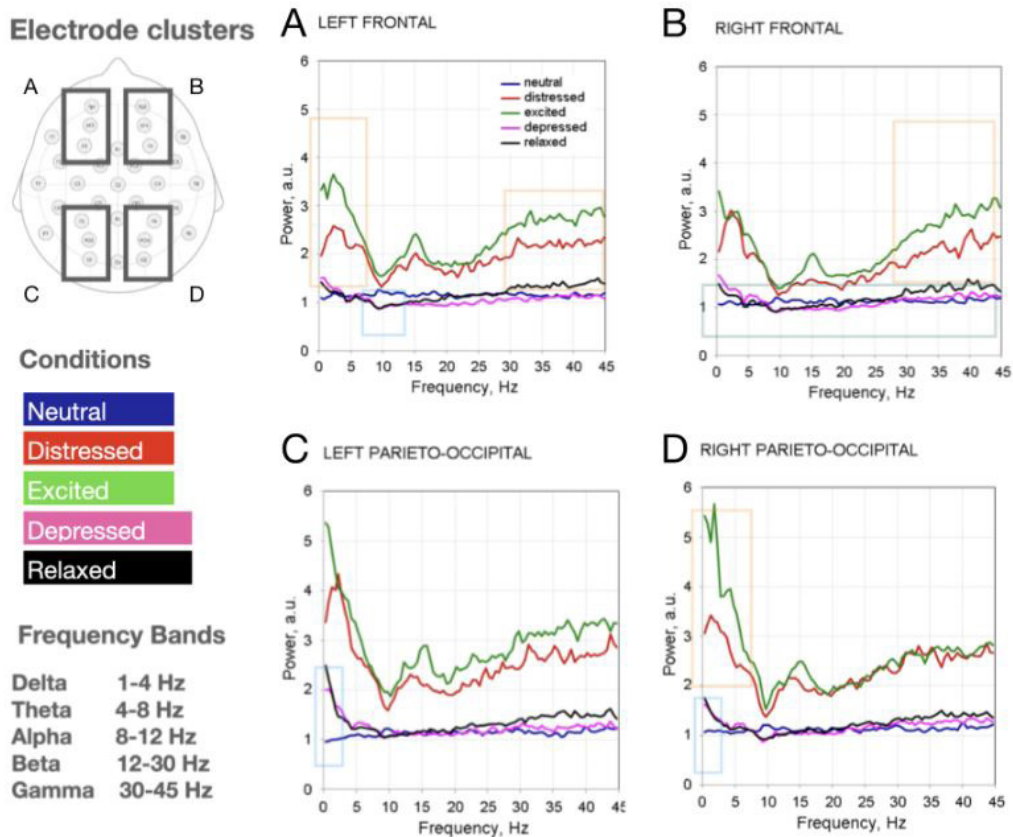


Figure 4: Top left, electrode clusters making up each ROI (A-D) corresponding to Left Frontal (A), Right Frontal (B), Left Parieto-Occipital (C) and Right Parieto-Occipital (D) brain regions. Left center, color key of conditions plotted in the diagrams. Bottom left, frequency band ranges. Diagrams on the right are plotted data representing spectral power of each expressive condition relative to Neutral from each ROI.

Each of the four diagrams represent an ROI, and the plotted data shows the power spectrum per expressive condition relative to the Neutral condition averaged together from all ten subjects over all 2000 trials. Here we were able to see small differences between contrasting conditions. In the High Arousal (HA) conditions Distressed and Excited, there were greater differences in the Delta-Theta range in ROIs A and D. There were also greater differences observed between the same conditions in the Gamma range, but between the ROIs A and B (see light orange boxes). As for Low Arousal (LA) conditions Depressed and Relaxed, nearly no differences could be seen relative to the Neutral condition, except in the Delta range in the ROIs C and D. Finally, a suppression of the Alpha band could be seen across all conditions and ROIs.

Despite the large amount of data collected (2000 trials), this study had a limited number of participants (10 subjects). Analysis by the neuroscientist colleagues from Taiwan (Pousson et al. 2023, 4352) revealed that EEG signals varied between individuals and sessions even though they were performing the exact same task – a property of the EEG signal known as non-stationary – because experience changes over time,

a task cannot be repeated in exactly the same way. Thus while these results cannot be generalized, they do provide an authentic early snapshot of regional brain activity during music performance with contrasting expressive intentions. Since EEG recording during music performance remains scarce, even a limited study such as this may be considered a valuable contribution to the scientific literature in both fields, inviting others to replicate or investigate further. This EEG dataset was later analyzed using connectivity measures, revealing dynamics of intra-brain information flow (Ghodousi et al. 2022, 4064). In line with our BCMI design objectives, additional work provided clues useful for developing software that detects and maps expressive intentions in real-time (Ghodousi et al. 2023, 2252).

CURRENT RESEARCH: EEG HYPERSCANNING INTER-BRAIN SYNCHRONIZATION DURING MUSIC INTERACTION

Soon after publishing the results of our first study, our EEG lab was able to acquire a second EEG system from the same maker (Enobio). This gave us the capability to run EEG experiments using the Hyperscanning (HS) technique in which two brain signals are recorded simultaneously (Acquadro et al. 2016). This technique enables psychologists using the EEG method to study human social interaction by observing the reciprocal influence of the signals during cooperation or competition in more ecologically valid conditions (Czeszumski et al. 2020, 3). Music interaction provides an excellent context for HS studies because it involves joint coordinated action and mutual adaptation over a temporal framework (Sänger et al. 2012, 1–2). Our new project utilized this new capability to study music interaction in subject pairs with future aims to harness measures of IBS for multi-user BCMI systems. With this aim in view, our main research objective was to characterize inter-brain dynamics of contrasting types of music interaction tasks, specifically problem solving (playing correctly) and problem finding (improvising) task types.

Various methods have been used in past studies to measure IBS during music making (Gugnowska et al. 2022, 4110–4127). In particular, Phase Locking Value (PLV) has been used to quantify phase alignment consistency between frequency-specific EEG signals from two brains to observe heightened levels of synchronization during rhythmic coordination (Lindenberger et al. 2009, 5–7) as well as desynchronization during motor alignment and joint attention (Jenson et al. 2020, 4; Lachat et al. 2012, 10–11). Another established method, Granger Causality (GC) has been used to determine the influence of one brain signal upon another. This method has been used in past studies to reveal leader-follower influences within a guitar duo (Sänger et al. 2013, 1) as well as asymmetrical role-specific patterns in pilots during flight simulation (Astolfi et al. 2011, 2338–2341). A limitation of past studies has been either a focus on symmetry without causality or a focus on uni-directional causality without considering reciprocal influence, leaving unresolved questions concerning leader-follower inter-brain dynamics during music interaction tasks. For example, how does a leadership role

emerge or submerge during improvisation? Or, how does the task goal and structure affect directional connectivity patterns between musicians during coordinated performance? From a neuroscientists perspective, there was an opportunity to integrate both PLV and GC methods in our approach in order to connect findings to past studies and potentially shed light on the present unknowns.

With these opportunities in view, a HS experiment protocol was designed to record EEG data during two contrasting music interaction tasks. We recruited 15 subject pairs, each including a professional percussionist who participated in all 15 recordings.

The first music interaction task was a rhythm learning task performed on electronic drum pads in which the percussionist leads by playing a predetermined 32-beat rhythm from a score while the other subject – without seeing the score – tries to play the rhythm by following and synchronizing with the percussionist over 30 repetitions divided into three runs of 10 trials each.

An experiment protocol (Fig. 5) was designed to include a Baseline (non-interactive resting state), and a Mechanical condition in which the subjects played straight 8th notes in unison, in order to isolate interaction task-specific EEG signals from non-interactive and body-movement related signals. A Rehearsal condition was also included to allow subjects to become accustomed to the recording sequence and the task. Next, in the Familiarization condition the percussionist plays the rhythm alone. Subsequently, in the Rhythmic condition the subjects play ten repetitions together. Finally, in the Recollection condition the other subject (not the percussionist) plays the rhythm alone. The sequence of Familiarization, Rhythmic and Recollection trials were repeated in three runs. The protocol was programmed in software to control the sequence of tasks while adding markers into both EEG data recordings simultaneously, 32 channels each, synchronized sample to sample at a rate of 500Hz.

192

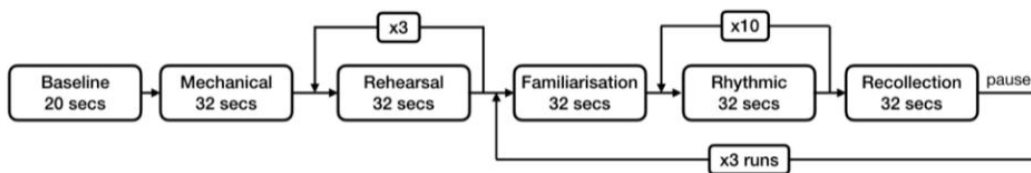


Figure 5: Sequence of the Rhythmic learning task used in our hyperscanning experiment protocol.

The 32 beat rhythm (Fig. 6) was composed in 4 phrases of 8 beats each, at a tempo of 1 beat per minute. Thus each Rhythmic trial lasted 32 seconds. Rhythmic complexity gradually increases across the 4 phrases: the first phrase is easy to imitate, while the fourth is difficult without access to the written score. This was intentional in the design in order to study the learning and synchronization process in the follower. Feedback from post-experiment surveys indicated that some subjects felt that this mode of learning was unfamiliar in academic settings where score reading is the predominant method of learning new music. However, they also acknowledged that it simulated a process of synchronization in group performance settings in which an ensemble

becomes more temporally aligned through repetition. Musicologists may also appreciate that the design simulates a natural method of learning by ear and imitation familiar across a wider range of musical cultures regardless of differing notation systems or emphasis on score-reading.

32 beat pattern
for Inter-Brain Synchronisation

Valdis Bernhof
Oct 2023

1 percussionist (leader with score)
1 musician (follower without score)

$\text{♩} = 60$

The musical score shows four sections (A, B, C, D) across eight measures. Section A starts with a simple pattern of quarter notes. Section B introduces eighth notes and sixteenth notes. Section C includes triplet markings. Section D features a complex pattern with many triplet markings. Vertical dashed lines indicate the start of each measure, numbered 1 through 8. The tempo is marked as quarter note = 60.

Figure 6: The 32-beat rhythm designed for the Rhythmic learning task used in this study. Complexity is increased over sections A-D.

The second music interaction task was an improvisation task in which the other subject leads using an instrument of their choice while the percussionist supports and responds on acoustic drums. The second task was repeated five times with a duration of two minutes each as shown in Figure 7.



Figure 7: Sequence of the Improvisation task in our study.

The percussionist recruited to the study was a student of the jazz department with many years of experience in improvisation. The other 15 recruits consisted of academic instrumentalists, musicologists, or teachers in training – with relatively less experience in improvisation. During their pre-experiment briefing, many subjects mentioned that they almost never have contexts to improvise in and that they felt a little nervous about being recorded while doing so. Having taken this into consideration, the percussionist was instructed to play a supporting role, allowing the other subject to

lead each improvisation. Further, the recording sequence was designed to allow for communication and planning before each improvisation trial. These considerations served to make the less experienced subjects feel more comfortable with improvising and to switch their task focus onto finding a coherent exchange rather than on playing correctly.

This HS experiment design enabled us to capture inter-brain dynamics occurring between all 15 subject pairs during both tasks, while keeping one subject (the percussionist) constant in order to compare differences between the other subjects more accurately. The complete technical details and analysis results from this dataset are in the process of publication this same year and we look forward to sharing that and proceeding towards applying the outcomes to multi-user BCMI system design as a future step. The following section describes outcomes from these two back-to-back investigations and their implications for BCMI system design.

OUTCOMES, IMPLICATIONS AND OPPORTUNITIES FOR BCMI APPLICATIONS

The outcomes of our first study yielded clues for classifying the ongoing EEG activity of a music performer into HA versus LA expressive states. In theory, since the spectral power of HA (Distressed and Excited) conditions were higher relative to Neutral than LA (Depressed and Relaxed) conditions, a BCMI system could be programmed to detect a user's expressive intentions. The numerical data used to plot the results in Figure 4 was used to define target values and thresholds for each expressive state (HA and LA) in each ROI within a visual programming software called Quartz Composer². This software is now deprecated but currently still enables us to visualize and map HA versus LA expressive intentions in real time while playing a music instrument. It achieved less than 30ms latency which made it suitable for live music applications, but adding 500–1000ms temporal smoothing was useful for avoiding occasional noise-induced fluctuations.

An early visualization employed a blue ball on a black field with a horizontal midline as shown in Figure 8. If higher HA values are detected in the ongoing EEG the blue ball rises above the midline, while higher LA values in the signal cause it to descend below the midline. This provided a straightforward means of visual neurofeedback for testing and mapping to musical or visual outputs which could be learned by a new user relatively easily.

² <https://developer.apple.com/documentation/quartz/quartz-composer>

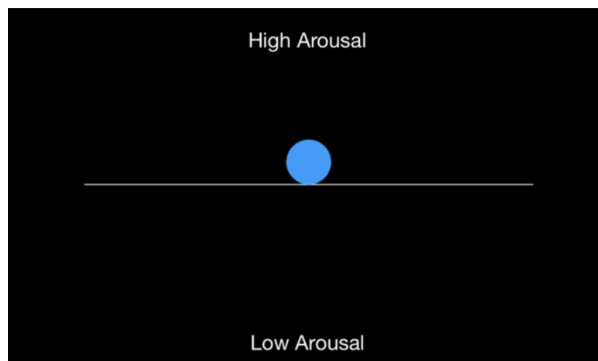


Figure 8: Neurofeedback visualization of a blue ball and horizontal midline dividing High Arousal and Low Arousal conditions. The blue ball moves above or below the line in response to the BCMI system user's ongoing EEG.

One implication of our limited sample size of 10 subjects was that thresholds defining HA and LA conditions may vary for new users. To overcome this, functions were programmed in the BCMI software to allow this to be adjusted for new users and new environments. A new user would begin by setting an individual threshold for Neutral, and then begin to modulate their expressive intentions between HA and LA to move the blue ball into the intended zone. If the blue ball moves not as intended, the user could then adjust their individual thresholds until it does move as intended.

195

This implies that like learning to play any musical instrument, a BCMI system does take a little time to get accustomed to. In my experience testing and demonstrating this system, it takes some people only 15 minutes to learn to manipulate the blue ball willfully, while it takes most people about 30–40 minutes to simply get used to it. Formal evaluation of this system achieved 70–84% accuracy over 3 rounds of testing with a new group of subjects playing different instruments. We saw potential for this BCMI system for live music performance applications and began testing it outside the lab in real concert settings. For some examples please refer to the next section of this article.

We expect our current EEG hyperscanning study to yield several potential opportunities for multi-user BCMI, possibly leading to applications in the wider BCI field. Specifically, an important future milestone will be to evaluate various task-relevant inter-brain synchronization (IBS) metrics for implementation in new multi-user BCMI software. The current analysis approach uses GC and PLV measures which will in turn inform the development of an IBS-based BCMI. More work is needed to implement real-time calculation of these metrics between multiple brain signals in software. We are optimistic that after identifying, deploying and refining this component, it will open up many new possibilities for musical expression and other forms of non-verbal communication.

Theoretically, if task-relevant levels of neural synchronization within a goal-directed team such as a music ensemble could be displayed back to them in real-time as neurofeedback, they could potentially learn to guide themselves more consciously

into a shared state of optimal performance, such as a group flow state. Two real-time IBS visualizations we developed for exploring this theory are shown in Figure 9. This opportunity to visualize or musify levels of group synchronization could also potentially serve as non-verbal cues for observers or audiences. For example, in the context of live performance, imagine a string quartet, each member with a spotlight on them which changes colors in response to their individual brain activity. As the colors modulate a viewer could observe moments of synchronization and desynchronization within the quartet as the music piece unfolds.

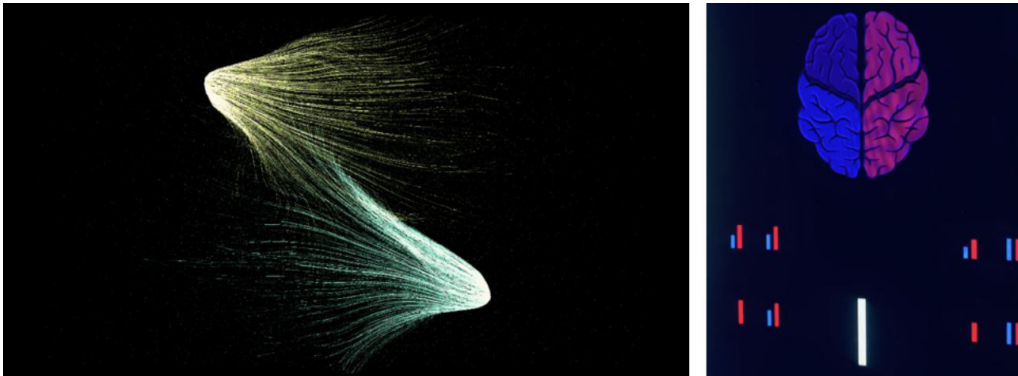


Figure 9: Left, video still of two particle systems driven by online EEG signals from two persons in which synchronization based on HA-LA conditions causes the particle systems to merge. Right, video still of a visual of a brain representing Alpha (blue) and Beta activity (red) from two persons in 4 brain regions each (red and blue bars). As activity becomes more symmetrical, the colors of the brain brighten and the white bar increases in length.

196

Our team also envisions the possibility of BCI systems that could potentially connect many brains to a shared network enabling EEG-driven forms of non-verbal communication. We see opportunity for such technology to use music or visual iconography as a non-verbal indicator of mood, perhaps similar to the way emoji symbols in digital text-based communication today are a form of emotive shorthand. The HS method has formed the basis for such technology to emerge, and efforts to visualize real-time inter-brain dynamics in performer-performer or performer-listener contexts is a direction of work which may contribute solutions towards wearable neurotech devices in the future enabling non-verbal networked communication. For example, we can imagine future scenarios in which a performer and an audience's inter-brain dynamics play a role in the narrative or stylization of a performance environment. Taking this one step further, when EEG hardware surpasses the limitations of current consumer grade devices, the potential will increase for wearable neurotech devices to become more commonplace methods for non-verbal communication between individuals and teams.

This project is still ongoing with a limited number of participants recorded each year consisting mainly of JVLMA student volunteers matching the study criteria. As always patience is necessary for neuroscience outcomes to bear fruit in the BCMI field.

BCMI DESIGN AND ARTISTIC APPLICATIONS: APPROACH TO ARTISTIC BCI

A BCMI system is a combination of EEG signal acquisition hardware, real-time classification software, and audio/visual feedback as shown in Figure 10. BCMI system designs described in published literature consist of various kinds of software programmed to transform and map the live EEG signal to control musical or visual outputs in real time (Miranda and Castet 2014, 221–254). In this section, several examples are described illustrating how our bridging gaps in interdisciplinary research manifested into artistic BCI applications outside the laboratory.

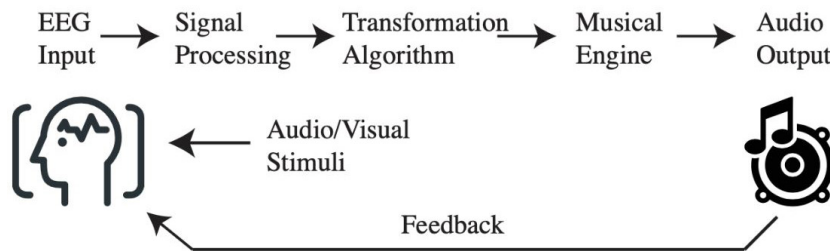


Figure 10: Typical components of a BCMI system perform the steps of EEG input, signal processing, algorithmic transformation, music control, and finally audio output which becomes real-time feedback. Additional audio/visual stimuli may also be presented or tasks may be given to test the interaction.

When crossing into the realm of artistic use, BCI has to play to the strengths of its chosen techniques to serve the narrative. Different BCI techniques provide different levels of active and passive control. Further, different mapping strategies can actuate different control types. In a many-to-one control type, many EEG features are mapped to control a single music parameter, whereas in a one-to-many type, a single EEG feature is mapped to control many music parameters. Some BCIs employ a mixture of both – a many-to-many control type. Evidently, planning an artistic BCI requires a well-chosen technique and control type appropriate for serving the overarching narrative of the artistic work.

An issue in the field of artistic BCI has been the clarity of the user’s intentions. A viewer must be able to perceive a relationship between the performer’s actions and the resulting sound or visual. If a BCI performer remains motionless as is often the case, how is a viewer to know if the output is actively or passively controlled? A challenge for the field has been to use BCI in such a way that enables a performer to do something easier than by manual means. In other words, if it is easier for a performer to play a note on a piano or raise a MIDI fader, why assign such triggers or controls to a BCI system? The following section includes a brief technical description of how BCI techniques and mapping strategies were implemented and how they addressed these issues and challenges.

MAPPING THE EEG SIGNAL TO CONTROL AUDIO VISUAL SYSTEMS

This section aims to provide an overview of our approach and our choices of BCI technique and control mapping for ease of understanding the examples in the next section. For full documentation of this BCMI software's design and testing processes please refer to Pousson's PhD dissertation available on our institution's website ³. To clarify how BCMI mapping may be practically achieved using currently available technology, the following terms are explained:

MIDI stands for Musical Instrument Digital Interface and is a communication protocol widely shared by analog, digital and virtual electronic music instruments. The value range of a MIDI CC signal is 1–127. It is typically used to enable communication or synchronization between different electronic music instruments, or used to configure master controls over multiple instruments. It may additionally be used to control visual parameters by driving graphical data visualizations or by manipulating effects and transitions on preloaded videos in live visual software such as VDMX ⁴.

CV stands for Control Voltage, the main method of controlling modular synthesizers. Each module in a modular synthesizer patch performs certain functions controlled using analog electrical voltages delivered by patch cables. Voltage ranges vary between system types, but common ranges are 0V to +5V, 0V to +8V, and -5V to +5V, with a peak-to-peak voltage of 10V. In modular synthesis, modules may function as a sound source, control or modifier. Players of such systems combine modules in creative ways to generate, sequence, filter, and otherwise modify sounds in ways that allow for explorations of atypical kinds of modulation and unique sound shaping that are not possible using prepackaged keyboard synthesizers.

DMX stands for Digital Multiplex and is a digital data stream like MIDI. It is typically used to control stage lighting and special effects machines. A standard DMX signal contains 512 channels with a value range of 0–255 for controlling parameters such as brightness, color, focus and movement. Devices that communicate using DMX are typically daisy-chained together with each device assigned a sequential group of channels.

These three communication methods provide a bridge between BCMI software and audio/visual systems and software types. The process of mapping can take place over several stages and software programs depending on what the final output is intended to be. For example, the BCMI software may be programmed to output a single string of MIDI CC values, and within any typical Digital Audio Workstation (DAW) software,

³ <https://www.jvlma.lv/aktualitates/savu-promocijas-darbu-aizstavejis-dzeikins-edvards-pusons>

⁴ <https://www.vidvox.net/>

this single string can be mapped to control multiple MIDI parameters of different ranges and behaviors. On the other hand, it would also be possible to calculate all the desired ranges and behaviors in the BCMI software itself before receiving MIDI CC values within a DAW on separate MIDI channels.

The choice of mapping strategy depends on what the user aims to control. This is similar to the process of designing a virtual music instrument in the node-based MAX/MSP⁵ software or creating a patch using analog modular synthesizers. There are many options for routing and controlling sound in both software and hardware. Some ways are more efficient and effective than others depending on how you want to play them.

Our most effective and accurate BCMI software so far was developed based on results from our first brain music study at JVLMA, described in the previous section. In line with typical BCMI systems described earlier (Fig. 10) the main components of our system perform the following functions in real-time:

- a) Receive an online EEG data stream,
- b) Structure and normalize the data stream into channels per electrode and amplitude values per frequency band,
- c) Compare ongoing values with HA and LA values within the four ROIs reported in our study and return a value representing percentage true for each expressive condition.
- d) Map HA and LA values to the y-axis position of the blue ball visual (Fig. 8) for immediate feedback as well as to any MIDI, CV or DMX control parameter. This technique enabled active control with accuracy evaluated between 70–84%. It employed a many-to-one mapping strategy to achieve a simple visual feedback (the blue ball). Since it was also possible to map the movement of the blue ball to many parameters, this mapping strategy could be also deployed as a many-to-many control type.

This BCMI design formed a core component for live performance applications where in practice a user would be able to run the software, receive their EEG signals over a network, and map the position of the blue ball to any number of musical or visual controllers. In effect, such a BCMI system could be used in place of live mixing or stage lighting engineers, handing over the responsibility of these support roles to BCMI where they may potentially serve as a reflection of the performer's ongoing neurological state. The following sections include 3 examples of how this design was implemented within artistic works.

Example 1: BCMI performance of a MIDI score

Despite its simplicity, this BCMI system was developed most recently and is included here as an example for its effectiveness in enabling any individual to experience levels of BCI control, regardless of music instrumental ability or even corporeal mobility – it could be used while motionless or in motion.

It was originally conceived as an interactive installation in honor of Estonian composer Arvo Pärt, and featured his piece *Für Alina* performed as a MIDI score looped on repeat. The music is minimal and meditative, using the tinntinnabuli style invented by Pärt – two voices walk in unison in harmony based on a triad rather than a scale, in lengthening then

⁵ <https://cycling74.com/products/max>

contracting phrases. The written score consists of a single page without instrumentation or note durations, and players are instructed to repeat it peacefully, in an elevated and introspective manner, in different octaves, articulations and dynamics.

These parameters could be controlled using our BCMI system by mapping levels of HA to increase tempo, and sound brighter timbre instruments on upper octaves; and LA to decrease tempo, and sound darker timbre instruments on lower octaves within a DAW (Fig. 11). The aesthetic result was envisioned to be an experience in which a user could sit or walk comfortably around a space while the piece modulates in response to their internal expressive intentions over several repeats.

Admittedly, active intentional control was not crucial to this design, and a MIDI playback rendition does fall short of conveying the nuances expected of expert human performance. Nevertheless, this BCMI design offers a convincing experience of BCI control to new users who are first learning how their EEG modulations behave. In the case of an individual user who may not be proficient at playing a music instrument, or a user who suffers from limited mobility, the ability to modulate ongoing parameters of a predetermined music piece was found to be an effective BCMI design. The following examples address these issues more directly at different levels.



Figure 11: Top left window, MIDI score arranged for several virtual instruments within a DAW. Bottom left window, raw EEG monitor (8 channels). Right window, BCMI software using our HA-LA (blue ball) algorithm. Levels of HA-LA control the tempo of the MIDI playback, and result in different combinations of virtual instruments playing in different octaves.

Example 2: BCMI timpani solo within an orchestral piece

In this example a BCMI system was employed within an academic piece *The Seat of Consciousness*⁶, composed by Pousson for the Latvian chamber orchestra *Sinfonietta Riga* which premiered on May 10, 2025. In this scenario, a solo part was to be performed by the composer using EEG signals amplified through a speaker cone placed on the surface of a 26-inch timpani. This concept was inspired by the groundbreaking piece *Music for Solo Performer* by composer Alvin Lucier in 1965 (Christopher et al. 2014, 1142), in which he amplified his EEG signal into percussion instruments.

As shown in Figure 12, this BCMI routed EEG signals from the performer's brain (A), to a computer (B), to an amplifier (C), to a speaker cone (D), to the timpani (E). The performer positions the speaker cone over the surface of the drum and controls the foot pedal (E) to modulate the pitch. The computer transformed the online EEG into audible rhythms the performer can willfully manipulate.

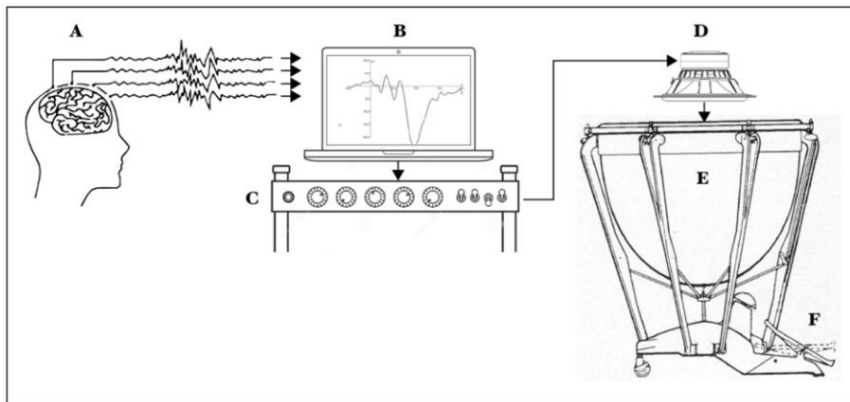


Figure 12: Steps of the BCMI system used to route EEG signals from a performer's brain (A) to a timpani (E) with a foot pedal (F) using a computer, amplifier and speaker cone (B-D).

The timpani solo appears at the beginning of the final movement and was notated as shown in Figure 13. The setup of the equipment and the result are pictured in Figure 14. To enter, the EEG Timpani player, wearing an 8 channel electrode cap, raised the volume on the amplifier allowing rhythms to sound through the speaker cone. The BCMI software calculated HA and LA values, transformed them into a MIDI Continuous Control (CC) value. A DAW software mapped the MIDI CC value to control the rhythmic density and pitch range of percussive attacks using Note Repeater and Arpeggiator MIDI effects in tandem. The resulting sound could be manipulated willfully, modulating from sparse, low pitched rhythms in simple time all the way to a dense complex polyrhythmic patterns with a wide range of pitches. This enabled the player to perform a range of constantly changing patterns throughout the solo. Situated within the narrative of the piece, the EEG timpani solo represented the inner mental process of creative work and aimed to express a human emotion of stillness in profundity, in beholding a complex subject.

⁶ <https://www.jachinpousson.com/single-post/the-seat-of-consciousness-premieres-at-ljmd>

30

M
♩ = 120

sord. 240 244

2 Trp.
sord.
fff

2 Hrn.
sord.
fff

1 Cl.
fff

1 B. Cl.
fff

1 Bsn.
fff

1 Chsn.
fff

32", 23"
Timp.
fff

202

Ad Lib.

EEG Timp.

M

Artificial harmonic slides
SP Sul G → MSP Sul D

Artificial harmonic slides
SP Sul G → MSP Sul D

Artificial harmonic slides
SP Sul C → Sul G → Sul D → Sul A

arco
Artificial harmonic slides
SP Sul C → Sul G → MSP Sul D → Sul A → SP

arco
Artificial harmonic slides
SP Sul E → Sul A → MSP Sul D → Sul G → SP

Vln. 1
mf → f + pressure

Vln. 2
mf → f + pressure

Vla.
mf → f + pressure

Vc.
pizz. fff → mf → f + pressure

Ch.
pizz. fff → mf → f + pressure

Figure 13: The entrance of the EEG timpani (outlined in yellow) in the orchestral piece “The Seat of Consciousness” composed by Pousson in 2025. The marking “Ad Lib.” gives the player freedom to improvise.

This BCMI system enabled a soloist active control with a many-to-one mapping strategy. The complexity of the rhythms striking the timpani were audibly beyond the capabilities of a human percussionist, enabling the user to do what would be otherwise impossible. While the performer remains motionless for reasons related to the narrative of the piece, the same technique could be used to enable a person with limited mobility to use it as a musical instrument. Within a DAW, a user could map HA-LA values to control any MIDI parameter or trigger, opening the possibility to perform, compose or produce using either live or recorded brain activity instead of faders to define automation curves.



Figure 14: Left, BCMI system setup from the performer's perspective. Right, view of the BCMI system in use from the audience's perspective.

The use of BCMI in this piece was subtle but aimed to position it effectively in the context of an orchestral work. Technically, the use of a computer and electronics places this piece on the border of electroacoustic works. Yet it does not fit in that category either since it does not involve a tape (playback) element, and does not require microphones or speakers. It only requires a power source for the amplifier- not more than that required to operate a vibraphone motor on a concert stage. We are fortunate to have modern ensembles such as *Sinfonietta Riga* who are willing to realize experiments such as these.

Example 3: BCMI mapping for live electronics

As aforementioned, a BCMI system can be mapped to control various electronic music and lighting equipment, as well as live visualizations using MIDI, CV and DMX signal communication.

The BCMI software in this example was developed specifically for interfacing with electronic music instruments during an artistic residency by a local modular synthesizer maker called Erica Synths⁷. We called this BCMI software "Neurosynth".

As shown in Figure 15, Neurosynth received 8 EEG channels (7 across the forehead and one in the back), from signal acquisition software Neuroelectrics Instrument

⁷ <https://garage.ericasynths.lv/articles/jachin-pousson/>

Controller⁸ (NIC), from the makers of the Enobio EEG system. It was programmed to output 16 EEG parameters as 16 continuous streams of MIDI CC values. A graphical user interface (GUI) was designed to display these ongoing values on a monitor for visual feedback, arranged in a horizontal row from left to right respective to their levels of active to passive BCI control. The far left parameter employed our HA-LA algorithm to output the most active control, labeled “Arousal” – a value ranging from 0-1 in which 0 is LA, 0.5 is Neutral and 1 is HA. Next to the right, HA values were labeled “Excite” and LA values “Calm”, in effect re-ranging the initial “Arousal” value to 0-1 for each condition. The “Global” value represented the average power across the entire EEG frequency band spectrum, here labeled Delta, Theta, Alpha, Beta and Gamma. The next three parameters labeled “Synch”, “Syn” and “Desyn” output values derived by comparing frequency band amplitudes between left and right brain hemispheres. The “Synch” parameter increases as the power spectrum becomes more symmetrical versus less symmetrical between the hemispheres. “Syn” and “DeSyn” re-range this value to 0-1 for each condition. The next five labels correspond to ongoing amplitudes in each spectral band from Gamma to Delta. The final four labels describe output values corresponding to average spectral power from all frequency bands grouped into four regions – “Front”, “Right”, “Left” and “Back”. Each of these parameters output MIDI values on 3 MIDI channels.

204

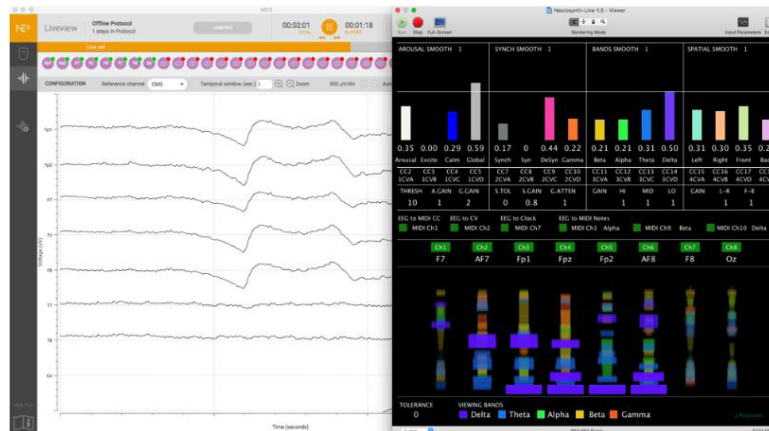


Figure 15: Left window, raw EEG monitor and signal acquisition in NIC software. Right window, Neurosynth software GUI with 16 EEG parameters displayed on top, MIDI and CV mapping displayed in the middle, and a waterfall type data visualization of synchronization events occurring between electrodes over a ten second window, color coded by frequency band.

MIDI channel 1 was assigned to output 16 simultaneous MIDI CC values (CC2-CC18) and these were mapped to control parameters such as Cutoff, Resonance and Envelope on four analog keyboard synthesizers and a drum machine through an audio interface with a 5-pin MIDI cable. MIDI channel 2 was assigned to output 16 CV values in 4 groups using a 4 MIDI-CV converter modules, which effectively retransformed the EEG signal back into voltage in a normalized range for controlling a rack of modular synthesizers. MIDI channel 7 was assigned to communicate with a DAW which provided the master

⁸ <https://www.neuroelectrics.com/nic2>

clock for the entire setup. This enabled modulating the master tempo of multiple connected devices using the brain signal alone – a technique we found to be saliently perceivable from the perspective of both the performer and a viewer.

Additionally, the data visualization at the bottom half of the screen was programmed to display the occurrence and strength (amplitudes) of synchronization events between each EEG frequency band and channel. Synchronization events (same frequency band and amplitude appearing in two or more locations) were rendered as colored bars representing each frequency band (Delta to Gamma) appearing in a downward scrolling waterfall type graphic over a ten-second window. These events could be mapped to trigger note-on and note-off MIDI commands, and could thus be used to play pitches of any predetermined scale, or rhythms determined by the density of synchronization events or even quantized to sound in metric time.

This software provided many options for mapping BCI control, both to and between keyboard and modular type systems. Figure 16 shows one of the mapping strategies employed using the Neurosynth interface, from the 8 channel EEG input on the left to hardware devices on the right assigned different roles and functions. In this setup the keyboards and modular system were planned to be played live but sound shaping parameters were controlled by MIDI and CV from Neurosynth. The computer's main role was sound control via MIDI, the keyboards main roles were sound sources while the modular system's role was mainly to modify the sound.

Neurosynth's debut live performance took place in August 2024 at the Erica Synths studio. The performance space also included DMX lighting, and so Neurosynth was updated to map HA-LA values to the intensity of red and blue lights respectively. Additionally, a visual artist on our team, Mārtiņš Dāboliņš, developed a liquid simulation visual which was projected onto the performer's head using head tracking tools and a video camera (Fig. 17, right). This visual changed colors and dynamics in real-time like a kind of aura or halo following the performer's head. This component was also BCI controlled, by patching an Open Sound Control (OSC) output from Neurosynth to the visual artist's computer over a network. The result enabled the performer to control the overall color of the stage and visual in synchronization with audio parameters. When correlated with master tempo, these visual modulations also became one of the most salient active BCI controls from the perspective of a viewer. See Figure 17 for images of the physical setup. The raw EEG signals were also displayed next to the Neurosynth window as seen in Figure 15 to monitor the input.

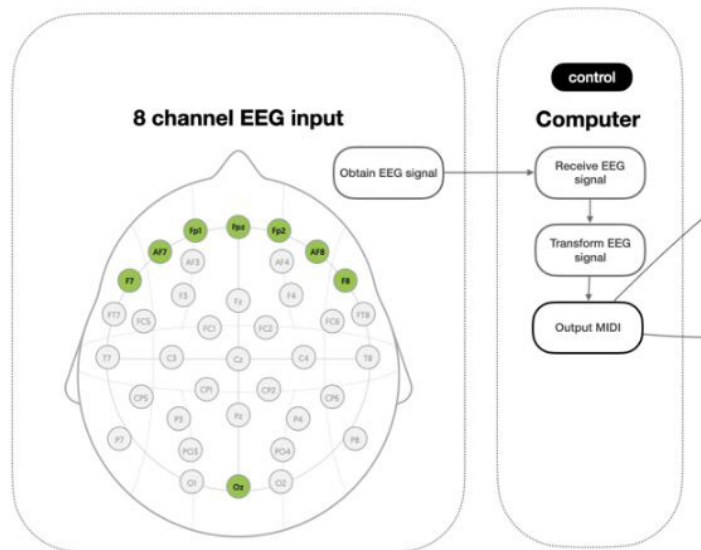


Figure 16: BCMI mapping strategy used by Neurosynth where EEG signals from 8 channels (F7, AF7, Fp1, Fpz, Fp2, AF8, F8, Oz) were received and transformed in a computer before being output as MIDI and CV to control and modify sounds played on analog keyboards and a modular synthesizer system.

206



Figure 17: Left, setup of 4 analog keyboards on a table and modular system installed on a wall. Middle, EEG acquisition software and Neurosynth running side by side. Right, performer using an 8 channel EEG headband to control music, light color and head-tracking visual projection.

The design and use of Neurosynth to connect to a maximum number of instruments in this setting resulted in versatile mapping tools for interfacing with electronic audio/visual systems in concert stage environments. In particular, the use of a range of active to passive parameters yielded several key observations. First, active control parameters driven by HA-LA values are most effectively mapped to salient parameters such as tempo and ambient lighting, enabling a viewer to perceive a direct relationship between the performer's brain activity and expressive intentions during performance. A linked modulation of temporal and ambient light color was particularly effective for this purpose. Second, passive control parameters driven by individual or averaged spectral frequency band power such as the Gamma-Delta parameter values, the regional power values, and the global power value were most effective when mapped to control the most subtle parameters in the audio signal. These mainly included modifier type modules such as filters, reverbs, and delays, which could be performed by both keyboard and

modular type synthesizers. Third, controls driven by hemispheric synchronization measures such as Synch values were most effective when mapped to modulate parameters with a middle level of salience such as cutoffs, resonances and envelopes. During performance, these modulations are especially audible during moments of switching focus from one physical electronic instrument to another. In particular, this interaction enabled something that was previously impossible – a brief yet noticeable change of timbre and articulation across many sound sources playing at once while in physical transition.

In summary, the three examples described in this section illustrate the potential for BCMI to find situationally appropriate roles in live performance in context of the narrative or intention of the work.

DISCUSSION AND RECOMMENDATIONS

The sciences and the arts have always inspired each other to innovate ways of uncovering or expressing truth, through empirical validity or aesthetic insight respectively. It is important to be persistent and objective when finding ways to work together towards our common goals. A systematic musicologist's role in these efforts is not only to be a mediator between scientists and engineers, but to bring focus to how such technology can benefit musical growth, and enhance music's ability to communicate expressive intentions.

The integration of systematic musicology and neuroscience through Brain-Computer Music Interfacing is more than a technological curiosity – it is a transformative step toward understanding and shaping human musical interaction. By prioritizing ecologically valid performance, expressive intent, and inter-brain synchrony, this research demonstrates that BCMI can evolve into genuine musical instruments rather than laboratory artifacts. The broader implication is clear: if musicians can learn to communicate through their neural states as fluently as through traditional instruments, then BCMI holds the potential to expand human expressivity, cooperation, and creativity.

Developing BCI techniques within the framework of embodied music interaction offers a key advantage – music communicates through an inherently ambiguous language, yet listeners perceive meaning. Consequently, learning to control a BCI through cooperative play emerges naturally in musical contexts, as users learn to express themselves by becoming aware of their own mental states, both in musical synchrony and in interaction with others.

We see the potential for BCMI innovations to benefit the wider field of BCI at the intersection of neuroscience and human-computer interaction. EEG hardware designed for use outside the laboratory such as on concert stages could be beneficial for industries looking to monitor EEG data in other noisy or challenging environments in real time, and even remotely over a network. This could lead to more advanced types of cooperative,

co-creative BCI for all kinds of creative teams, or be used as a form of faster-than-speech communication between remote team members. The ability to monitor EEG synchronization metrics of any kind of team could further lead to the discovery of new methods of group neurofeedback for optimizing goal-directed performance.

What sets this research apart from earlier projects which have musified or visualized the EEG is that our approach is from the perspective of music instrument designers. We ask how brain activity can be leveraged in a way that supports rather than hinders human expressivity and emotion during play, and how this may enable new forms of creative cooperation or catalyze group flow through non-verbal cues. These questions aim to empower creativity. In contrast, many innovators in this field approach EEG musification techniques as a tool for wellness or mindfulness applications focusing on self-monitoring or the entrainment of mental states. A novel contribution in our work was the increased effectiveness of mapping strategies, achieving new levels of expressive interaction, in turn enabling BCI to play more intentional, situationally appropriate and salient roles within the narrative of artistic performance or creative processes.

While the concept of using the human EEG signal to create art has been explored increasingly especially over the past two decades, there are still knowledge gaps to fill and technological challenges to overcome before BCI can become more widely available to creative communities.

New collaborations are needed with EEG hardware design and software engineering experts to develop prototypes suitable for either artistic research or performance. More research is needed on this frontier – increased datasets with increased variety of task focuses in order to discover more reliable and accurate active control techniques. Additionally, expertise is needed to evaluate, improve and innovate algorithms for real-time EEG signal processing and transformation steps. If researchers and innovators in these fields can increase inter-disciplinary collaboration towards these aims, we see potential for BCMI system technology to be widely integrated into music instruments of the future, enabling unforeseen levels of expressive agency reflecting neurophysiological states.

Systematic Musicologists, composers, performers, art educators and therapists are needed to help to guide the development of this emerging technology in a direction that catalyzes human creativity and cooperation, and that builds community and culture.

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