Generating an Integrated Musical Expression with a Brain–Computer Interface

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ABSTRACT

Electroencephalography (EEG) has been used to generate music for over 40 years, but the most recent developments in brain–computer interfaces (BCI) allow greater control and more flexible expression to use new musical instruments via EEG. We developed a real-time musical performance system using BCI technology and sonification techniques to generate chords with organically fluctuating timbre. We aimed to emulate the expressivity of traditional acoustic instruments by adding “non-coded” expressions that were not marked in the score. The BCI part of the system classifies patterns during neural activity while a performer imagines a chord. The sonification part of the system captures non-stationary changes in the brain waves and reflects them in the timbre by additive synthesis. In this paper, we discuss the conceptual design, system development, and the performance of this instrument.

Keywords

Brain–computer interface (BCI), qualitative and quantitative information, classification, sonification

1. INTRODUCTION

A musician can dream about an ideal performance without any physical limitations, where the performer plays with the expressivity imagined in their mind. At the heart of this dream, however, there is an assumption that the human mind is capable of free expression (our imagination of music is supposed to be spontaneous, without constraint, and in perfect accord) but its physical rendering, i.e., the musical performance, is a limited delivery of the overall imagined performance. In this project, we attempted to capture a glimpse of the imagination of music to generate a performance with the aim of making music an organic expression that reflects the lively and subtle transitions of psychological states.

NIME'13, May 27 – 30, 2013, KAIST, Daejeon, Korea.

Thus, we developed an expressive musical instrument for concert performances, which renders musical chords with organic nuances (dynamics and timbre) in real time based on the brain waves measured during musical imagination, using a brain–computer interface (BCI) technique and sonification techniques. A study by Herholz et al. showed that there are overlapping areas in the brain during melody perception and imagery[5]. Thus, we aimed to employ these types of brain waves related to musical imagery for generating musical expression. Table 1 shows the features of our BCI instrument compared with an acoustic instrument.

A traditional acoustic instrument is highly expressive when it has been mastered after extensive training. A survey showed that humans add expressive performance actions that are not marked in the score, which can also be found in pre-20th century music. Many instruments also provide the ability to change intonation, vibrato, and timbre in an expressive manner [8]. We consider that this expressivity often relies on the capacity for *intended codes*, such as notes and rhythms, and *non-coded expressions*, such as dynamics, timbre, and subtle micro-timing.

Using our new instrument, we aimed to generate the same degree of expressivity based on coded and non-coded information from brain waves. The coded musical elements (e.g., musical chords) are generated based on the classification of brain waves, *i.e., qualitative information* whereas the non-coded, organic nuances (e.g., dynamics and timbre) are generated from the transitional characteristics of the brain waves, *i.e., quantitative information.* In addition, our instrument has a video projection element that corresponds to the state of the brain waves, which aims to reflect the music imagery.

This instrument was developed for practical musical expression but we hope also that it has the potential for understanding the neural activity in the brain when a player is engaged in musical expression.

1.1 Advantages of Using Electroencephalography to Produce Music

Electroencephalography (EEG) is a method for measuring the electrical activity produced by brain neurons. Compared with other biological methods, it has some appealing points for use in music generation. The time resolution of the data acquired using EEG is very fine, which makes it suitable for generating musical changes over time. Other methods used to observe brain activity, such as fMRI and

Table 1: Comparison of Musical Expressivity Using an Acoustic Instrument and our Instrument

	Acoustic Instrument	Our BCI Instrument
Control	Physical motion to generate physical sound	Imagery, psychological motion to induce neural activity
Music (coded, qualitative)	Notation	Chords generated by classification (BCI)
Music (non-coded, quantitative)	Non-notated articulation	Dynamics and timbre as sonification (sonification)
Vision	Gestural presentation	Video corresponding to music imagery

MEG, require extremely large equipment, whereas many portable and handy EEG systems are available on the market. However, the most attractive aspect of EEG is that the brain waves reflect thoughts and emotional states. Thus, producing music using EEG may reveal actual emotions, which is an attractive prospect.

In addition, research into BCIs has been growing in recent decades. The ultimate goal of BCI is to build a system that reads human thoughts, which can provide a bridge between the brain and an external device. Many analytical methods have used BCI to identify thought states and emotions in the mind. Thus, BCI provides the possibility of extracting the patterns of musical imagery from neural activity.

1.2 Related Work

Many notable composers have attempted to produce music using EEG. The American composer Alvin Lucier was the first person to use EEG as a source of music. In his piece *Music for Solo Performer* (1965), alpha waves were used to vibrate percussion instruments. David Rosenboom is another famous composer who used EEG for sound and music creation. One of his contributions was the use of a biofeedback process during musical performances where he made the brain state of the performer audible [14].

In recent years, many artists have worked using EEG, which has been facilitated by the smaller size and low price of the latest EEG devices. For example, Angel [1] produced interactive art using EEG data, while visual effects and sounds were generated based on brain, heart, and respiration signals by Filatriau [3]. Some notable projects have been presented at past NIME conferences [4, 10, 11, 13].

Previous studies have used BCI for music creation. Miranda developed a brain–computer music interface (BCMI) that comprised a MIDI-controlled mechanical acoustic piano controlled by EEG using generative musical rules[12]. Another group, *The MiND Ensemble*, delivered stage performances using a portable EEG system[1]. In their performances, psychological parameters were estimated from brain waves and assigned to musical parameters.

1.3 Problems and Solutions

All of the aforementioned studies developed functional methods for music performance using EEG, which allowed the audience to perceive musically expressed neural activities from various perspectives. These studies typically analyzed brain waves and presented them as sounds. Thus, they extracted useful information from neural activity and mapped it to musical parameters, before presenting the music to audiences. In our study, we considered the different types of biosignal information that can be obtained and used for music generation.

1.3.1 *Qualitative and Quantitative Information*

Most biosignal information can be classified as qualitative or quantitative.

The book *Biomedical Signals and Sensors I* by Eugenijus Kaniusas provides a historical account of the methods used for collecting biosignals [7]. Early research was based on verbal descriptions provided by patients, which were subjective and qualitative. By contrast, the use of technical tools to make biological measurements has reduced the level of subjectivity because these approaches are based on quantitative data. Interestingly, a flute teacher, Francois Nicolas Marquet, attempted to code heart pulses as a musical notation. This case is regarded as a combination of qualitative and quantitative data.

Kaniusas regarded the difference between qualitative and quantitative information as a problem of subjectivity versus objectivity. When considering the use of biosignals for musical expression, this approach facilitates a clear mapping to musical parameters. This is because music may be considered to be composed of coded information, such as notated pitch, and non-coded information, such as non-notated articulation, which correspond to qualitative and quantitative data, respectively. Therefore, playing an instrument is considered to be an action where the player produces sounds based on their subjective (or sometimes subconscious) ideas and feelings, whereas the sound produced by the player conveys both qualitative and quantitative information to the audience.

In this context, we propose a method that integrates the qualitative and quantitative information obtained using EEG before its use for musical expression. The major advantage of our approach is that quantitative information can be contextualized using qualitative information. Both qualitative and quantitative information are then mapped onto musical parameters, which are coded musical elements and non-coded organic nuances, respectively. In this manner, the integrated information is transformed into musical expression.

2. GOALS

Based on the solutions proposed above, we aimed to produce a musical performance by integrating the qualitative and quantitative data extracted from EEG outputs. Thus, a player wearing an EEG system imagines chords, i.e., sets of musical notes, in their mind. Our BCI instrument extracts various patterns and characteristics from the EEG data and converts them into sounds and visual images. The amplitude of the EEG data affects the timbre of chords via sonification. This allows music to be played using brain waves as an instrument where the sounds reflect the brain activity during the imagination of music. Based on this idea, we aimed to design our instrument for practical use in musical performances, such as a concert.

To accomplish this goal, the *Brain dreams Music (BdM) Project* was initiated in April 2011 by researchers from diverse domains, such as music composition, neuroscience, and computer science. This group has conducted research to develop this new instrument.[2]

[1] http://www.themindensemble.com/

[2] http://brain-dreams-music.net/

3. DESIGN AND IMPLEMENTATION

3.1 Design of the Performance

Before formulating the specifications of the instrument, we designed the overall process of our musical performance as follows. Figure 1 shows the overall procedure used to acquire EEG data, which are processed and delivered to the audience using BCI. In this procedure, the instrument estimates the music imagined by a player and generates sounds and visual images automatically in real time.

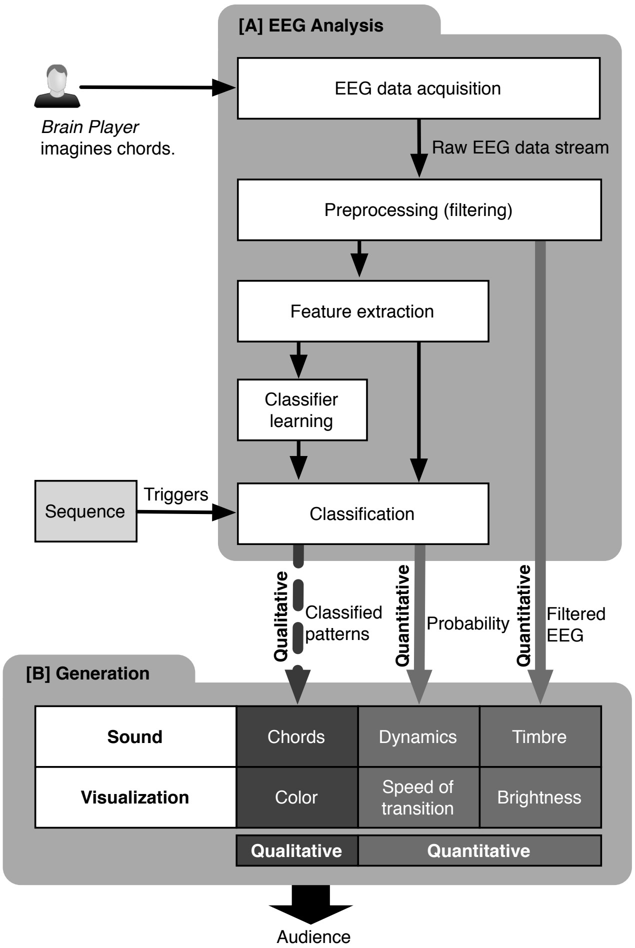

Figure 1: Schematic diagram of the procedure used during musical performances with BCI. The extracted qualitative and quantitative information are integrated to produce sound and vision representations.

The procedure can be divided into two stages, which are indicated by the grey areas [A] and [B] in the figure.

3.1.1 EEG Analysis ([A])

The first stage is the EEG analysis. The computer estimates the patterns of imagined musical chords as qualitative information and extracts other quantitative information. These processes are conducted in parallel.

EEG Data Acquisition.

First, the player known as the *Brain Player* wears an EEG cap and imagines notes as if they were actually playing music. In the latest version, the player selects one of four different types of chords during each imagination session. The time frame for each chord is 3 s and it is repeated more than 10 times. During this period, the EEG signal is recorded by the computer.

Preprocessing.

The acquired EEG data are processed using a band-pass filter during the *Preprocessing* stage. This removes any artifacts, including noise components such as the electric hum noise or the pulse from the heart.

Feature Extraction, Classifier Learning, and Classification.

To estimate the patterns imagined by the player, it is necessary to make the computer learn the correlations between features in the brain-wave patterns and the imagined chords. However, the electrophysiological brain signals captured non-invasively via the human scalp using EEG are non-linear and non-stationary. We addressed this problem by combining two methods, i.e., the common spatial patterns (CSP) method is used for feature extraction and binary linear discriminant analysis (LDA) is used for classification.

To determine the order of processing, common features are extracted from each imagery pattern using the CSP *feature extraction* process and the filtered EEG signals. CSP has been used widely in BCI research to identify linear spatial filters for extracting discriminative brain activities during two different mental imagery tasks. We used CSP to find the optimal spatial filter for each imagery class, which maximizes the average energy of that particular class while minimizing the other remaining classes.

The extracted features are stored and organized during the *classifier learning* process. This learning process is conducted every time before a performance because the state of the brain waves changes on a daily basis and the computer needs to be recalibrated.

After the computer learns the feature of the EEG pattern, it is ready for classification. During the *Classification* process, the newly acquired data is classified according to four predefined patterns. To implement a multi-class machine learning approach, we utilized a cascade of LDA classifiers in a one-versus-all configuration. During each classification step, "a winner takes all" method is applied by choosing the best one-versus-all classification posterior probability result. The results of the pattern analysis and the probability are used to generate sounds and visual images.

In another path, the filtered EEG signal is used directly without processing as a source for sonification.

This instrument applies different information properties using the classification results and the filtered EEG signals as qualitative and quantitative information, respectively.

3.1.2 Generation ([B])

Various types of data produced by the *analysis* process are mapped to the parameters of the sounds and images, which are used to generate an entity that will be received by the audience.

Sound.

The synthesizer receives the classification results and generates the sound of chords with an additive synthesis. The dynamics of the sound vary depending on the probability value, which indicates the degree to which the classification results are likely to be correct. Each note sound comprises one fundamental tone and seven overtones, i.e., a total of eight sinusoidal waves. These waves are multiplied by processing the raw EEG data from each electrode channel, and modulated. To enhance the effect of timbre, the overtones are set with various degrees of inharmonicity with weighting coefficients for each overtone. This is an extension of overtone mapping [15] and it produces a unified sound effect when integrating multichannel EEG signals. Finally, each overtone is played separately from eight speakers, which mixes all of the overtones in the acoustic space.

The timing of the imagery, EEG recording, classification, and onset of the playing sound are triggered by the score data. The score is made by the composer beforehand using four predefined chords. During our performances, the player attempts to play music by imagining each chord a short time before it is actually played. This can be slightly confusing for the player and the player has to know when to imagine. To address this situation, we implemented a time-synchronized score display. The score reflects the composer's musical intention to some extent. After the score display starts playing, each chord the player needs to imagine is shown on the player's iPad in sequence so the player can concentrate on imagining that chord. In other words, the score simply indicates the timing but does not affect any of the result of the analysis, including the classification results.

Visualization.

Visual images are also generated by the same information used to produce sounds and they are presented to the audience at the same time.

The positional arrangement of the electrodes is shown on the screen so the audience can observe the classification results and the brain activity simultaneously. Thus, the overall color represents the classified pattern, the transition speed of the color reflects the probability value, and the brightness of each electrode position represents the amplitude of the filtered EEG signal.

3.2 Implementation of the Instrument

To implement this performance paradigm, we constructed the BCI shown in Figure 2.

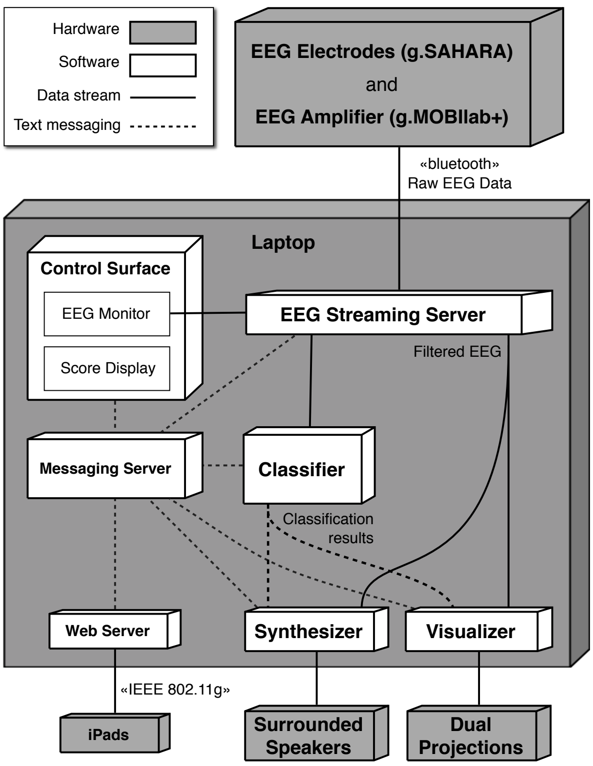

Figure 2: Diagram of the system architecture of our BCI instrument.

Table 2: List of Programming Languages and APIs Used in the BCI

Process	Languages and APIs used
EEG Streaming Server	MATLAB
Messaging Server	Java
Web Server	Node.js
Classifier	MATLAB
Synthesizer	Max/MSP
Visualizer	Java, OpenGL
Control Surface	Java, OpenGL

3.2.1 Hardware

A mobile wireless EEG amplifier *g.MOBIlab+* was used in combination with dry EEG electrodes *g.SAHARA* manufactured by *g.tec*[3]. g.MOBIlab+ also sent EEG data to the computer in real time at a 256 Hz sampling rate via Bluetooth serial communication. Unlike typical wet EEG electrodes, the g.SAHARA dry electrodes did not require gel or paste. Thus, the preparation was faster and there was no need to wash the head after use. The number of measurement positions was up to eight each time and the arrangement could be changed freely. Based on the results of our experiment using another wet 32-point EEG electrode system, we selected the eight channels that worked the most efficiently and effectively. The portability of this EEG device indicated that it was suited perfectly to our musical performance.

We used a MacBook Pro with Windows 7, which was installed with BootCamp. Some physical MIDI controllers were connected to it to allow more convenient control during performances. In addition, we used iPads to provide a visual presentation of the imagery and to give other accompanying acoustic instrument players cues that facilitated musical synchronization.

Finally, the generated sound was played by 8-channel speakers and the visualization was shown on dual screen. The multi-channel speakers produced an acoustic space where the audience could hear precise changes in brain activity.

3.2.2 Software

The software configured several internal processes using multiple programming languages and APIs (Table 2).

Each process operates independently in parallel while information is exchanged between processes via networking. The exchanged information belongs to two types, i.e., a stream of EEG data and text messages. Both types of data are transferred via UDP. Three types of servers, i.e., an *EEG Streaming Server*, Messaging Server, and Web Server were developed using MATLAB and Node.js[4].

All of the controls required for a performance are handled on the *Control Surface*. A preview monitor of the raw EEG waveforms and the topographic map, the controls used for the classification process, and the sequencer for playing control were implemented on the Control Surface (Figure 3).

4. PERFORMANCE

We conducted five performances during 1.5 years using this musical BCI, including domestic and overseas events. Three of the performances were given in large concert halls in international conferences or exchange concert programs. Others were parts of concerts in small lecture rooms.

The latest performance took place at Kubus (Cube) in Zentrum für Kunst und Medientechnologie Karlsruhe on

[3] `http://www.gtec.at/`
[4] `http://nodejs.org/`

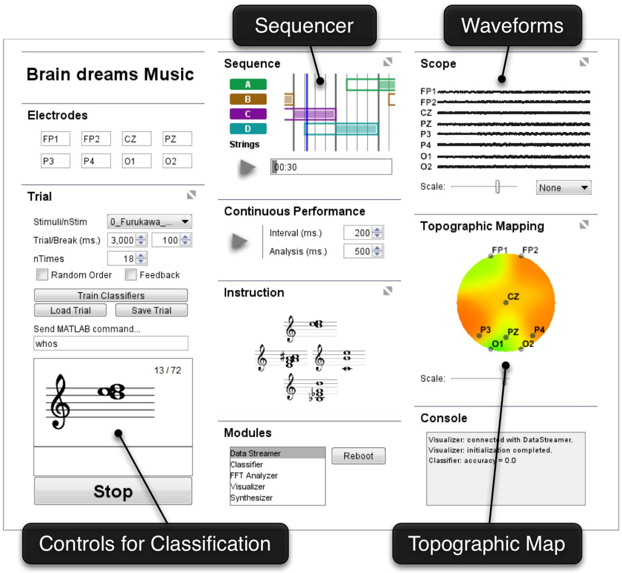

Figure 3: Screenshot of the control surface.

September 2012[5] (Figure 4). The seating capacity was around 50 and eight speakers were arranged at regular intervals on the stage. Visual projections were displayed on a large central screen for the *Visualizer* and another monitor at the side displayed the *Control Surface*. We provided a demonstration and gave a live performance to verify the usability and expressivity of our instrument. The brain player was not allowed to move his body so the audience could see that the player was sitting still. During the performance, the audience listened to the sound and recognized certain musical structures that partly reflected the player's intentions. The fluctuating timbre also allowed the audience to perceive dynamical changes in brain activity. The visual images synchronized with sounds allowed the audience to appreciate the brain activity.

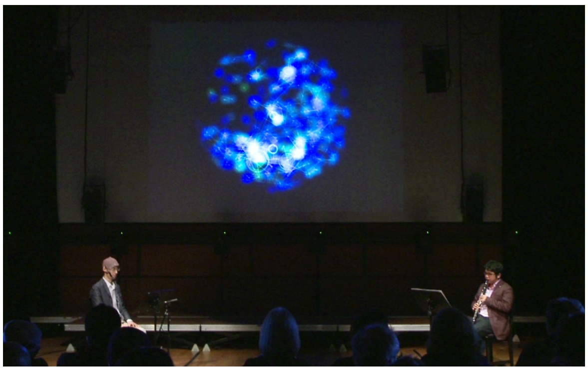

Figure 4: Performance at Zentrum für Kunst und Medientechnologie Karlsruhe (ZKM), September 2012.

The brain player usually plays music with one or several accompanists. We have delivered performances on many occasions with a clarinet player and once with a string quartet. These acoustic instrument players interact with the sound generated by the brain player, which produces a dialogue between the players (Figure 5).

Video recordings and pictures of past performances have been uploaded on the website of the BdM Project.

[5]http://on1.zkm.de/zkm/stories/storyReader$8116

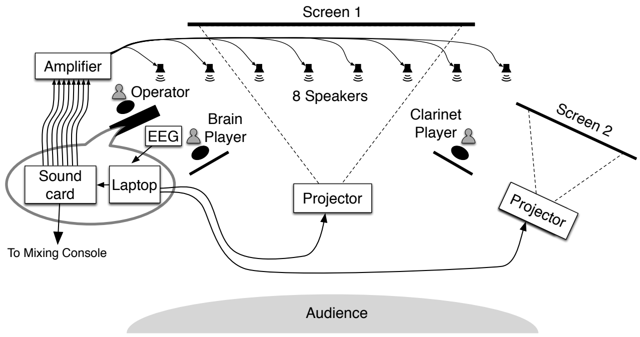

Figure 5: Stage diagram.

5. DISCUSSION

In this section, we discuss the technical novelty of BCI for communicating the aesthetics of musical expression.

5.1 Analysis methods

The classification algorithm was the main factor that improved our instrument. The average accuracy was 50% using four classes. This result was sufficiently high because the chance level was 25%. During a musical performance, however, it was difficult to get the feeling that the player was controlling the instrument on their own. Thus, the accuracy needs to be improved to enhance the level of control. Possible solutions are to improve the algorithm or to use more advanced methods such as SVM or cross-validation. These techniques may improve the results but they require more computational time, which is why methods need to be devised for online implementation. Another possibility is making improvements using portable EEG devices. Experimental evaluations are required in future to address these points.

Two other possible analytical methods could be used in our BCI instrument. First, music is a temporal art form so temporal change appears to be an important element in the imagery of music, which may also involve the anticipation of different musical states. In future, we could use an EEG analysis method to evaluate the causal relations between channels relative to time, such as a *Directed Transfer Function* where imagery patterns related to changes in the music might be captured.

Another possibility is the measurement of emotional states. The components of music are considered to be associated with specific types of emotions so the imagery of music may contain images of emotional states. Previous studies have measured biological signals to estimate emotional states during musical performances [6, 9]. Estimating emotions during musical imagery would be a novel application of the BCI instrument.

5.2 Musical Elements Used for Imagery

The choice of the music elements used for imagery is important from another perspective. In our instrument, we used long tones of chords with a certain degree of complexity. We used them because the player could imagine the temporally steady state of a sound and each chord had a characteristic that was distinct from another. We conducted an experiment to compare various types of musical elements during imagery and determined the classification accuracy. We assumed that a steady-state imagery while sustaining chords was favorable for our classification method, which analyzed the pattern of specific time frame in the EEG data.

5.3 Improvement of Human Imagery

The computer we used was not responsible entirely for the classification results because the human operator also had room for improvement. If the human operator could imagine the music better, the computer would find it considerably easier to classify the brain-wave patterns. Many instruments require training before an expert musical performance can be produced and this was also the case for our instrument. Thus, if the controllability could be increased by user imagery enhancement training, it would be closer to its ideal form and the user could produce an instrument with a wide range of expressivity. At present, we have not verified whether non-musicians with a limited ability for imagining music can operate the instrument. If we can develop a methodology for learning musical imagery, this would open up the possibilities of brain music performance by many people. A previous study demonstrated that brains learn to control BCI adaptively citeblake:control. This type of human self-transformation process based on interactions with an instrument may improve expressivity.

5.4 Evaluation

As described above, we consider that it is always important to explore the effectiveness of musical BCI by coupling an analysis method with imagery elements and human imagery enhancement. These issues can be verified by technical evaluation in a scientific manner.

However, yet another type of evaluation is still required, which is the artistic meaning of the musical performance itself and the results produced by that performance. For example, it is not clear whether the player might exhibit better musical expression of the neural musical imagery with bodily movement. Davidson and Correia showed that the body is vital for the generation of expressive ideas about music, as well as being essential for the physical manipulation of the instrument[2]. Thus, we would like to compare physically embodied performances with disembodied brain performances.

6. CONCLUSION

We developed a BCI-based musical instrument that uses a combination of qualitative and quantitative information, i.e., the classification of musical imagery and the sonification of brain activity. This instrument was designed for use during a concert performance. It is our dream to convert natural expressions such as the mental images of emotions or memories directly into musical imagery, which would be free from physical constraints. This goal has only been partly achieved so far, but this was a first step that helps to elucidate the relationship between musical expression and the performance intent. As mentioned in Section 5.4, the multidimensional evaluation of this project need to address scientific and artistic issues. Thus, we will continue to explore our experiments and performances interactively because they are the most fascinating parts of this project.

7. ACKNOWLEDGMENTS

This research was conducted as a joint research project between JST, ERATO, Okanoya Emotional Information Project (OEIP), Tokyo University of the Arts, and University of Tsukuba. The author would like to thank Ryu Nakagawa (Tokyo University of the Arts) for his help with visualization, as well as Reiko Hoshi-Shiba (The University of Tokyo), Hidefumi Ohmura (OEIP), and Gen Hori (Asia University) for advice related to the experiments and analyses.

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