

Toward Direct Brain-Computer Musical Interfaces

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ABSTRACT

Musicians and composers have been using brainwaves as generative sources in music for at least 40 years and the possibility of a brain-computer interface for direct communication and control was first seriously investigated in the early 1970s. Work has been done by many artists and technologists in the intervening years to attempt to control music systems with brainwaves and - indeed - many other biological signals. Despite the richness of EEG, fMRI and other data which can be read from the human brain, there has up to now been only limited success in translating the complex encephalographic data into satisfactory musical results. We are currently pursuing research which we believe will lead to the possibility of direct brain-computer interfaces for rich and expressive musical control. This report will outline the directions of our current research and results.

Keywords

Brain-Computer Interface, BCI, Electroencephalogram, EEG, brainwaves, music and the brain, interactive music systems.

1. INTRODUCTION

Human brainwaves were first measured in 1924 by Hans Berger [3]. Today, the EEG has become one of the most useful tools in the diagnosis of epilepsy and other neurological disorders. The fact that a machine can read signals from the brain has sparked the imaginations of scientists, artists and other enthusiasts, and the EEG has made its way into a myriad of other applications. In the early 1970s, Jacques Vidal did the first tentative work towards a system interfacing the human EEG to a computer. The results of this work were published in 1973 in a paper entitled *Toward Direct Brain-Computer Communication* [27]. This domain of research is known as Brain-Computer Interfacing (BCI) and there are an increasing number of researchers worldwide working in the field. Vidal's work was followed by many other attempts at BCI

which had varying degrees of success. For example, in 1990, Jonathan Wolpaw and colleagues developed a system to allow primitive control of a computer cursor by subjects with severe motor deficits. Subjects were trained to use their EEG to move the cursor in simple ways [28]. For recent reports on BCI research please refer to the special issue of IEEE Transactions on Biomedical Engineering published in June 2004 (Vol. 51, #6).

We are focused on the development of BCI systems for musical applications and thus pay special attention to the development of appropriate techniques geared to real-time music systems. One might call such systems Brain-Computer Musical Interfaces (BCMI).

As early as 1934, a paper in the journal *Brain* had reported a method to listen to the EEG [1] but it is now generally accepted that it was composer Alvin Lucier, who composed the first musical piece using EEG in 1965: *Music for Solo Performer* [13]. Pioneers such as Richard Teitelbaum [25], David Rosenboom [23, 24] and a few others produced compositions and a number of interesting systems and pieces. In 1975 David Rosenboom edited a remarkable book on the topic [22] and more recently one of the current authors, Andrew Brouse, published a comprehensive review on using brainwaves to produce music [6].

Our research builds on the work developed by these pioneers in a number of ways. Firstly, we are employing and developing more sophisticated analysis techniques to harness the EEG signal. In addition, we are developing new psychophysical experiments in order to gain a better understanding of the EEG components associated with musical cognition and methods to train subjects to generate such EEG components. Finally, we are developing generative techniques especially designed for musical composition and performance with a BCMI. This paper focuses on the first and the latter. More information on our psychophysical experiments can be found in [15, 16].

Before we proceed, note that the BCI research community understands that a BCI system is a system that allows for the control of a machine by explicitly thinking the task(s) in question; e.g., control a robotic arm by thinking explicitly about moving an arm. This is an extremely difficult problem to solve. The system presented in this paper does not address this type of explicit control which would be even more difficult in the case of music. We are not interested in a system that plays a melody by thinking the melody itself. Rather, we are furnishing our systems with Artificial Intelligence in order to allow them make their own interpretation of the meanings of the EEG patterns. Such machine-interpretations may not always be accurate or realistic, but this is exactly the type of human-machine interaction that we are addressing in our work.

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2. THE ELECTROENCEPHALOGRAM

Neural activity generates electric fields that can be recorded with electrodes attached on the scalp. The electroencephalogram, or EEG, properly refers to the visual plotting of this signal, but currently has come to connote the method of measurement or just the electric fields themselves. These electric fields are extremely faint, with amplitudes on the order of only a few microvolts. In order to be displayed and/or processed, these signals must be greatly amplified [17, 19].

An EEG derivation is measured as the voltage difference between two electrodes on the surface of the scalp, with a separate ground to reduce common-mode interference. The EEG expresses the overall activity of millions of neurons in the brain in terms of charge movement, but the electrodes can detect this only in the most superficial regions of the cerebral cortex. The EEG is a difficult signal to handle because it is filtered by the meninges, the skull and the scalp before it reaches the electrodes. Furthermore, the signals arriving at the electrodes are sums of signals arising from many possible sources, including artifacts like the heartbeat, muscle contractions and eye blinks. Although experts can diagnose brain malfunctioning from raw EEG plots, this signal needs to be further scrutinized with signal processing and analysis techniques in order to be of any use for our research.

There are a number of useful approaches to quantitative EEG analysis, such as power spectrum, spectral centroid, Hjorth, event-related potential (ERP) and correlation, to cite but five. A brief non-mathematical introduction to EEG power spectrum and Hjorth analyses is given below due to their relevance to the systems introduced in this paper. A discussion on other analysis techniques and how they have been used in neuroscience of music research can be found in the given references [4, 10, 11, 18, 26].

2.1 Power Spectrum Analysis

Power spectrum analysis is derived from techniques of Fourier analysis, such as the Discrete Fourier Transform (DFT). In short, DFT analysis breaks the EEG signal into different frequency bands and reveals the distribution of power between them. This is useful because the distribution of power in the spectrum of the EEG can reflect certain states of mind. For example, a spectrum with salient low-frequency components can be associated with a state of drowsiness, whereas a spectrum with salient high-frequency components could be associated with a state of alertness. There are five recognised frequency bands of EEG activity, also referred to as EEG rhythms, each of which is associated with specific mental states: delta, theta, alpha, low beta and high beta rhythms. There is, however, some controversy as to the exact frequency boundaries of these bands and about the mental states with which they are associated.

Also related to power spectrum analysis is the spectral centroid analysis which calculates the spectral “centre of gravity” of the signal; that is, the midpoint of its energy distribution. It is a measure of the average frequency weighted by amplitude. This is usually averaged over time.

2.2 Hjorth Analysis

Hjorth introduced an interesting method for clinical EEG analysis [9], which measures three attributes of the signal: its activity, mobility and complexity. Essentially, it is a time-based amplitude analysis. This method is interesting because it represents each time step (or window) using only these three attributes and this is done without conventional frequency domain description. The signal is measured for successive epochs (or windows) of one to several seconds. Two of the attributes are obtained from the first and second time derivatives of the amplitude fluctuations in the signal. The first derivative is the rate of change of the signal’s amplitude. At peaks and troughs the first derivative is zero. At other points it will be positive or negative depending on whether the amplitude is increasing or decreasing with time. The steeper the slope of the wave, the greater will be the amplitude of the first derivative. The second derivative is determined by taking the first derivative of the first derivative of the signal. Peaks and troughs in the first derivative, which correspond to points of greatest slope in the original signal, result in zero amplitude in the second derivative, and so forth.

Activity is the variance of the amplitude fluctuations in the epoch. Mobility is calculated by taking the square root of the variance of the first derivative divided by the variance of the primary signal. Complexity is the ratio of the mobility of the first derivative of the signal to the mobility of the signal itself. A sine wave has a complexity equal to 1. Figure 1 shows an example of Hjorth analysis. A raw EEG signal is plotted at the top (C:1) and its respective Hjorth analysis is plotted below: activity (C:2), mobility (C:3) and complexity (C:4). (Figure 1.)

There is no clear agreement as to what these measurements mean in terms of mental states. It is common sense to assume that the longer a subject remains focused on a specific mental task, the more stable is the signal, and therefore the lower is the variance of the amplitude fluctuation. However, this point questions the possible affects of fatigue, habituation and boredom, which we have not yet accounted for in our research.

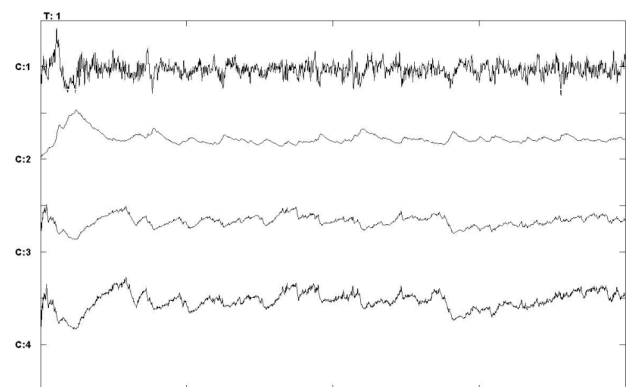


Figure 1. An Example of a Hjorth analysis.

3. THE BCMI-PIANO SYSTEM

The BCMI-Piano falls into the category of BCI computer-oriented systems. These systems rely on the capacity of the users to learn to control specific aspects of their EEG, affording them the ability to exert some control over events in their environments. Examples have been shown where subjects learn how to steer their EEG to select letters for writing words on the computer screen [5]. However, the motivation for the BCMI-Piano departed from a slightly different angle from other BCI systems. We aimed for a system that would make music by guessing the meaning of the EEG of the subject rather than a system for explicit control of music by the subject. Learning to steer the system by means of biofeedback would be possible, but we have not systematically investigated this possibility yet. We acknowledge that the notion of “guessing the meaning of the EEG” here is simplistic, but it is nevertheless plausible: it is based on the assumption that physiological information can be associated with specific mental activities or states [21, 2].

The system is programmed to look for information in the EEG signal and match the findings with assigned generative musical processes corresponding to different musical styles. For example, if the system detects prominent alpha rhythms in the EEG, then it might activate certain assigned processes that generate musical passages in a given style.

The BCMI-Piano is composed of four main modules: braincap, analysis, music engine and performance. The EEG is sensed with 7 pairs of gold EEG electrodes on the scalp, roughly forming a circle around the head. In this case we are not looking for signals emanating from specific cortical sites but to sense the EEG over the whole surface of the cortex. The electrodes are connected to a biosignal amplifier and a real-time acquisition system. The analysis module is programmed in Matlab and Simulink [14] to perform power spectrum and Hjorth analyses in real-time. The analysis module generates two streams of control parameters. One stream contains information about the most prominent frequency band in the signal and is used by the music engine to generate the music. In the current version, the system activates rules for two different styles of music, depending on whether the EEG indicates salient low-frequency or high-frequency components. The other stream contains information about the complexity of the signal and is used by the music engine to control the tempo of the music.

The core of the music engine module is a set of generative music rules, each of which produce a musical bar, or measure. The system works as follows: every time it has to produce a bar, it checks the power spectrum of the EEG at that moment and activates rules associated with the most prominent EEG rhythm in the signal. The system is initialised with a reference tempo (e.g., 120 beats per minute), which is constantly modulated by the signal complexity analysis (i.e., Hjorth analysis). The music engine sends out MIDI information for performance. We have implemented a demonstration using a Yamaha Disklavier piano.

In order to have greater control over this system, we are developing methods to train subjects to achieve specific EEG patterns in order to play the BCMI-Piano system. We have initial evidence that this can be made possible using a technique commonly known as biofeedback. Biofeedback is when biological signals are converted to some auditory or visual display which in turn affects the performer’s physiological state. As a result the subject can learn to modify their physiological state and thus

subsequently gaining greater control of the biological signals which it produces. Biofeedback technology has been used to treat and control a number of conditions including migraine headaches, epilepsy and attention deficit disorder. In addition it has been explored as a means of artistic exploration by performers, composers and artists [22, 23, 24].

The aim of our current research in this area is to create a methodology to train subjects to use BCMI technology through the use of biofeedback. If the results of this research are valid, this could lead to more independent expressive control during music composition and performance.

4. CONCLUSION

Our research work in this area owes an historical debt to the pioneering works of people such as David Rosenboom, Richard Teitelbaum and Alvin Lucier, but extends those tentative experiments with new possibilities for much finer granularity of control over real-time musical processes.

The work presented in this paper is the result of multidisciplinary research, ranging from neuroscience and medical engineering to music technology and composition. We acknowledge that our research so far has only suggested some tentative directions in a potentially vast field. There remain many cumbersome issues to be resolved before we can realise our ultimate goal: an affordable, flexible and practically feasible Brain-Computer Musical Interface.

Key issues still need to be addressed, notably, the task of interpreting the meaning of the EEG. Although powerful mathematical tools for analysing the EEG already exist, we still lack a good understanding of their analytical semantics in relation to musical cognition, however, continual advances in the field of cognitive neuroscience [20] are increasingly shining light upon these obscurities. Once these issues are better understood we will be able to program our devices to recognise patterns of cognitive activity in the brainwaves and thus trigger appropriate musical algorithms associated with such patterns. Some preliminary work in this regard has been reported to date [15, 16].

Another aspect which needs to be addressed is the non-ergonomic nature of the sensing technology for measuring the EEG which can be awkward and uncomfortable to wear. New electrode technology coupled with ‘smart fabrics’ could lead to increased comfort and portability of the equipment.

We also see many possibilities for innovations in the hardware design of EEG capture devices. Given current electronic technology it should be possible to build wearable EEG amplifiers with built-in measurement, signal processing and wireless data transmission.

Significant reduction in the cost of a functional BCMI is also possible by increasing using commodity hardware and software such as personal computers, USB A-D interfaces, WiFi and/or Bluetooth wireless devices and miniaturised biosignal amplifiers.

We are actively pursuing collaborations with other developers to advance these goals.

5. REFERENCES

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