BRAIN MUSIC SYSTEM :THE ROLE OF AN AFFORDABLE BRAIN MUSICAL INTERFACE IN DIGITAL MUSIC MAKING

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ABSTRACT

Music-making has normally been associated with manual activity apart from the creative "cortical activity" (for example , playing the piano or holding a guitar both need the use of hands) . Clinical equipment such as Electroencephalography (EEG) , made biofeedback a possibility for music-makers but still restricted its use to the few musicians that could afford such an expensive device. This paper describes a system named "Brain Music System" which is a novel , affordable and powerful system that is able to generate musical outputs based on information collected through an EEG collecting device. The research is influenced by the works of Professor Eduardo Reck Miranda, where different frequency bands trigger corresponding piano notes through, and the complexity of the signal represents the tempo of the sound. The accuracy of the musical conversion has been established through experimental work, where data of participants of a pilot group were gathered and analysed in order to determine which musical properties should be associated with the right brainwave type. The uses of such a device can be extremely beneficial when it comes to "inclusion" of people with manual disabilities in music-making.

1. INTRODUCTION

We know that "Sound is a regular mechanical vibration that travels through matter as a waveform" which exhibits all characteristics of longitudinal waves. (Kurtus).Sound waves with specific characteristics can be viewed as music. Alterations of ordinary sound in tone, note, time durations etc. create melody or music. The words of N'Diaye "a distributed network of brain areas has been repeatedly evidenced in timing tasks" identify musical touch of brain waves and activities. (N'Diaye, Garnero and Pouthas). Each state of brain is represented by certain waves called brain waves of which Gamma, Beta, Alpha, Theta and Delta are the recognized brain waves. Gamma waves (30 to 70 Hz) are produced while "processing of various attended stimuli…. From an EEG point of view, they will be present mostly while a subject is awake, but they will always be supported by other waves in the beta, alpha, theta, or delta ranges." (Instant meditation: The Concept). Usual considerations are given to main brain waves excluding supporting gamma waves. Brainwave activity tends to fall into four groups: beta, alpha, theta and delta. These categories are associated with the rapidity of oscillation (frequency) of brainwaves.

It may be asked why usage of sound waves itself are adopted, rather than light or visual rays. This can be resolved by understanding that EEG signals can be easily represented by sound waves due to similarity of both in many of their characteristics. The selection of sound waves instead of light or visual rays is due to the properties of light itself. "Light is composed of transverse waves in an electromagnetic field....The denser the medium, the greater the speed of sound. The opposite is true of light.... Sound travels through all substances, but light cannot pass through opaque materials." (Comparison of Light Waves with Sound Waves). The stated properties of light makes it inappropriate to be compared with EEG signals which are more alike sound waves.

2. NEURAL SIGNALS AND SOUND-PROCESSING

The sonification of EEG is of great value to the developers of musical applications: weather technologies or software solutions. On the other hand, this study recognized the importance of looking at this subject from a theoretical point of view as it helped in choosing the best methods of measuring, analyzing and converting brainwaves.

There are various distinct processes involved in converting neural signals to sound signals or sonification of neural signals. "Analyzing multichannel EEG signals using sounds seems a natural method: using a sonification of EEG signals.... perceive simultaneously every channel, and analyse more tractably the time dynamics of the signals – hoping to gain new insights about the brain signals." (Vialatte and Cichocki). The sonification of neural signals is done in various steps having separate sets of procedures. "This process consisted of the following stages:

1. Data acquisition
2. Data pre-processing:
3. Intermediate representation (the creation of visual and sonic map);
4. Visualization and sonification (Brouse et al, 9)

2.1 Brain Wave Conversion

A number of methods are available to be employed in analysing the various factors involved in transforming brain waves to music. Power spectrum analysis (PSA) and Discrete Fourier Transform (DFT) techniques are suitable in our context. "The Fourier Transform of the Auto correlation Function is the Power Spectrum." (Nyack). Power spectrum is used in analysing various images which finds application in this investigation as well. The first step in PSA is to Fourier transform the image I(x, y) and calculates the square modulus of the FT to generate the power spectrum, p (u, v).

$$p(u,v) = |FT[I(x, y)]|2 \quad \textbf{(1)}$$

(Power Spectral Analysis)

In order for us to obtain the active PSA , the FT array is rearranged according to frequencies in a way "that the zero frequency is in the centre of the array, the 1st quadrant is in the upper right, the second in the upper left, etc." (Power Spectral Analysis).
The resulting array was later converted to get values from 1.0 to 10.0 whose logarithm to base 10 is obtained.

The array obtained was then used to obtain the required equivalent; here brain waves underwent power spectrum analysis to get music equivalent for them. Discrete Fourier Transform (DFT) is another procedure carried out. "The Discrete Fourier Transform (DFT) allows the computation of spectra from discrete-time data... in discrete-time we can exactly calculate spectra." (Johnson). This definition itself explains the relevance of this method in our analysis of brain waves. Accurate computation is significant for conversion of brain waves to music waves so that least redundancies result.

2.2 Brainwave Collection and Analysis

The method adopted for data collection can be seen through the transformation of the EEG data, which was collected by an EEG collecting device as raw data. The approach is influenced by the interface described in the article Brain-Computer music interface for composition and performance by Eduardo Reck Miranda, where different frequency bands trigger corresponding responses to the recording device (Hofstadter, 2009) Installation of an EEG unit poses many restrictions like size and cost , which led us to adopt the usage of a device named pendant EEG. "Pendant-EEG is a lightweight 2 channel EEG unit that can be clipped to your clothing and connects to your computer via a wireless receiver." (Pendant-EEG).

The communication essential for the application is given through wireless technique with efficiency by this. Our application can be relied with confidence on pendant EEG as "it can reliably process signals from 0.1 to 56 Hz." (Pendant-EEG).

3. BRAIN MUSIC SYSTEM

The system used in the current project is built on the basis of the LORETA algorithm discussed about by Filatriau et al. (2007, p. 2). In more detail, the system design includes three major stages, i. e. EEG collection, digital signal processing, and MIDI representation.

This system design permits collection of the EEG waves of the participants' brains with the help of electrodes placed on their both hemispheres. Next, the data collected is processed with the help of the LORETA algorithm (Filatriau et al., 2007, p. 2), and after this the system produces MIDI files on the basis of analogies between the qualities of EEG waves and specific musical notes.

As seen from the above statement (Filatriau et al., 2007, p. 2)., the LORETA algorithm plays a crucial role in the operation of the system design This algorithm is based on four major criteria defined and calculated as first, it is necessary to measure the potential of EEG wave occurrence, Φ. Second, the value of the sources producing those EEG waves, φ, is measured. The third and the fourth criteria that help in estimating the second point are the lead field matrix, G, and the rate of additional noise, ŋ (Filatriau et al., 2007, p. 2):

$$\Phi = G\,\varphi + \eta \quad \textbf{(2)}$$

At the same time, Ito et al. (2006, p. 1153) propose a slightly different formula that includes the role of mental change in sound stimulation, S, and the additional noise, N, for the calculation of Y, the time series data:

$$Y = S+N \quad \textbf{(3)}$$

In any case, both formulae require additional calculations, and Filatriau et al. (2007, p. 2) provide rationale for them, arguing that the bayesian formalism fits the goal of defining the value of the sources producing those EEG waves from the above formula. So, the design system discussed here uses the following formula to obtain the final data that are later sent to the sound synthesis module (Filatriau et al., 2007, p. 2)

$$P(\varphi/\Phi) = P(\Phi/\varphi)P(\varphi) / P(\Phi) \quad \textbf{(4)}$$

The data obtained through the above formula are ready for processing with the help of the LORETA algorithm that includes four stages:

1. **Sending the data to the sound synthesis module;**
2. **Associating the brain zones with cognition, visualization, and movements;**

3. Creation of dipoles from the calculated data;
4. Computing the dipoles and using them as features for creating the respective MIDI files (Filatriau et al., 2007, p. 2).

Thus, the use of the LORETA algorithm is the basis on which the performance of the discussed system design is founded and the scheme described in figure 2.1 becomes possible with the use of this cheaper technology :

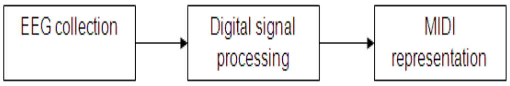

Figure 1. Brain Music System Technology flow

At this point, the system's design performance follows this scheme and uses the LORETA algorithm to enable the researchers to convert the EEG waves into MIDI

4. PILOT STUDY

The results for ten subjects undergoing a regular recording of 15 second active blocks using the Brain Music System (as described by Attard Trevisan & Jones) with a Pendent EEG collecting device were collected and presented in the table below. The four different brain waves i.e., Alpha, Beta, Delta, and Theta were color-coded as green, red, yellow, and blue respectively. The table below presents the average values of the four forms of EEG waves for ten subjects undergoing 15 seconds of useful recording blocks.

Objectives of the Study

1. Check if there are common patterns and levels of Brainwave activity in EEG outputs which can be optimally used in the musical process of the Brain Music System
2. Compare Output Brainwave levels by the"modified LORETA" with published literature studies

4.1 Results

EEG	subject 1	subject 2	subject 3	subject 4	subject 5	subject 6	subject 7	subject 8	subject 9	subject 10
Alpha	3.37	3.36	3.29	3.06	3.23	2.88	2.95	2.13	3.52	3.22
Beta	5	4.91	5.21	4.64	4.95	5.03	5.09	5.09	5.02	4.97
Delta	2.89	2.83	2.61	2.42	2.41	2.45	2.93	2.61	2.23	2.88
Theta	3.76	3.34	3.45	3.94	3.59	3.34	3.83	3.97	3.83	4.07

Table 1. Results of Pilot Study with the mean result recorded for each Brainwave type of every subject..

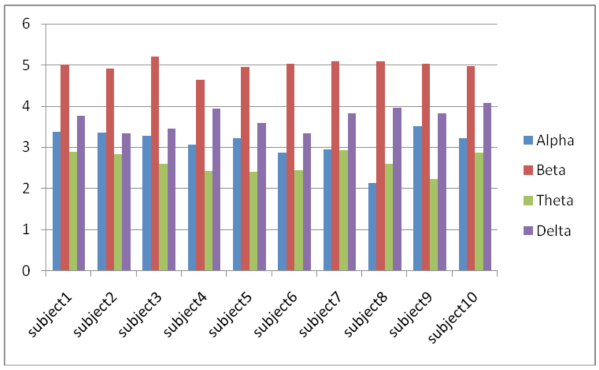

Figure 2. Graphical representation of Pilot Results with the mean result recorded for each Brainwave type of every subject..

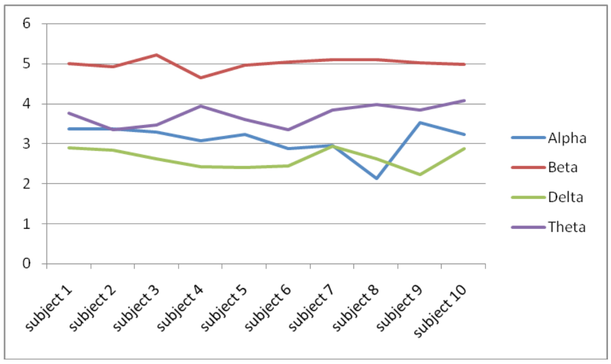

Figure 3. Graphical representation of Pilot Study results with the trend of the most stable results recorded for each Brainwave type.

5. DISCUSSION OF RESULTS

The linear Band Frequency Graph 2 shows that throughout the analysis of brain waves, the Beta wave presented as the most significant form of brain with the highest mean wave followed by Theta and Alpha waves respectively. The least form of brain wave was the Delta wave which had consistently lower figures in most of the subjects. According to the linear graph, Delta is statistically insignificant in this study in awake subjects and is thus deemed not relevant to include it. The means of the relevant bands recorded in the table above were analyzed and the results presented as Band Frequency Graph 1 (figure 2) and Band Frequency Graph 2 (figure 3) .They clearly indicate which of the bands had the most stable output, in order to further confirm which bands should be given priority for its role in the brain music system. The results show that the Beta waves have the most stable output, followed by the Alpha and the Theta waves.

Throughout the analysis of brain waves, the Beta wave presented as the most significant form of wave with the highest mean wave followed by Theta and Alpha waves respectively. The least form of brain wave was the Delta wave which since the experiment needed subjects to remain assertive had consistently lower figures in each of the ten subjects .

In this study, the Beta wave provides the best avenue for the study of the interaction between a musical piece and the brain. The results indicate that the left frontal regions of the brain are more involved in processing as shown by the higher mean of the Beta range. The right hemisphere may also be increasingly engaged with higher frequencies of the Beta wave. The Beta range can be used to indicate the part of brain that is involved in processing a particular kind of music. The Theta band showed coherence in pattern in the ten subjects and that coherence increased symmetrically, except in just few cases. The Alpha band was characterized by more coherence decreases and extending over longer distances than other bands.

The interpretation of increases in coherence advances the theory of increasing cooperation between two regions of the brain. Decreases on the other hand indicate that mental process under investigation requires lower collaboration between the two regions in order to perform optimally. Changes in gravity centers of coherence clearly indicate particular significance of the regions involved for processing information and how other cortical regions are involved. In the case of decreases, the region concerned may decouple from other cortical regions. Visual data processing studies have substantiated this view and can be applied to the alpha band as is the case in this study. In other words, attentive listening needs increased attention and suspends the freely floating thinking that could be assumed to take place upon EEG at rest; the two processes lead to parcellation of the cortex in that frequency band that is concerned in general attention processes. Moreover, it could also be that cortical coherence is reduced for an increased information exchange with subcortical sites. “As far as the behaviour in the Theta band is concerned, it was found to be fairly characteristic in processes where memory takes a momentous part (in this case, the violoncellist knew the piece by heart and thus, mentally anticipated every single phrase)” (Hellmuth et al.).

Conversely, emotion is also reflected by coherence. Machleidt et al shows that different bands may be adjacent to different domains of sensory signal processing. It is worthy noting that the extensive twisting of the cortex and the electrical conductivities of tissue layers may cause the electric features of the surface EEG not to be displayed fully. However, characteristic coherence patterns can be found.

6. CONCLUSION

From this study, common patterns and levels of Brainwave activity in EEG outputs can be optimally used in the musical process of the Brain Music System , thus helping in recreating a melody that is unique and fully adapted on the mood of the person using the system . The stratification of the different elements of the EEG can help to find out which band is most significant in the musical process of the Brain Music System. International Jazz musician Charlie Parker described music as being “your own experience, your thoughts, your wisdom“. This study shows that even people that cannot contribute physically to music-making can transmit all those 3 musical features to an audience.

4. REFERENCES

[1] E D Adrian and B H C Matthews (1934), The Berger Rhythm: Potential Changes from the Occipital Lobes in Man, Brain, 57, 4, pp. 355-85.

[2] C Anderson and Z Sijercic (1996), Classification of EEG signals from four subjects during five mental tasks, Solving Engineering Problems with Neural Networks: Proceedings of the Conference on Engineering Applications in Neural Networks (EANN’96), London, UK.

[3] G Assayag and S Dubnov (2004), Using Factor Oracles for Machine Improvisation, Soft Computing, 8, 9, pp. 604-610.

[4] H Berger (1929), Über Das Elektrenkephalogramm Des Menschen, Archiv für Psychiatrie und Nervenkrankheiten, 87, pp. 527-70.

[5] N Birbaumer, N Ghanayin, T Hinterberger, I Iversen, B Kotchoubey, A Kubler, J Perelmeouter, E Taub and H Flor (1999), A spelling device for the paralysed, Nature, 398,pp. 297-298.

[6] D Cope (2001), Virtual Music. Cambridge, MA: The MIT Press.

[7] D Giannitrapani (1985). The Electrophysiology of Intellectual Functions. Basel: Karger.

[8] C Guger and G Pfurtscheller (1998), EEG based brain-computer interface (BCI) running in real-time under Windows, Electroencephalography and Clinical Neurophysiology (Proceedings of 9th European Congress of Clinical Neurophysiology) 106, 1, pp. 91-100.

[9] B Hjorth (1970), EEG analysis based on time series properties,Electroencephalography and Clinical Neurophysiology, 29, pp. 306-310.

[10] T Kohonen, P Laine, K Tiits and K Torkkola (1991), A Nonheuristic Automatic Composing Method, In Music and Connectionism (P Todd & D G Loy, Eds), Cambridge (MA): The MIT Press.

[11] A Lucier (1976), Statement On: Music for Solo Performer, In Biofeedback and the Arts, Results of Early Experiments (D Rosenboom, Ed), Vancouver: Aesthetic Research Center of Canada Publications.

[12] E R Miranda, S Roberts and M Stokes (2004), On Generating EEG for Controlling Musical

Systems, Biomedizinische Technik, 49, 1, pp. 75-76.

[13] E R Miranda, K Sharman, K Kilborn and A Duncan (2003), ‘On Harnessing the Electroencephalogram for the Musical Braincap’, Computer Music Journal, 27, 2, pp. 80-102.

[14] K E Misulis (1997), Essentials of Clinical Neurophysiology. Boston (MA): Butterworth-Heinemann.

[15] E Niedermeyer and F H Lopes da Silva (Eds.) (1987), Electroencephalography, 2nd edition. Munich: Urban and Schwartzenberg.

[16] I Peretz and R J Zatorre (2003), The Cognitive Neuroscience of Music. Oxford: Oxford University Press.

[17] H Petsche and S C Etlinger (1998), EEG and Thinking. Vienna: Austrian Academy of Sciences.

[18] D Rosenboom (Ed.) (1975), Biofeedback and the Arts, Results of Early Experiments. Vancouver: Aesthetic Research Center of Canada Publications.

[19] D Rosenboom (1990), The Performing Brain, Computer Music Journal, 14, 1, pp. 48-65.

[20] R Teitelbaum (1976), In Tune: Some Early Experiments in Biofeedback Music (1966-1974), In Biofeedback and the Arts, Results of Early Experiments (D Rosenboom, Ed), Vancouver: Aesthetic Research Center of Canada Publications.

[21] J J Vidal (1973), Toward Direct Brain-Computer Communication, In Annual Review of Biophysics and Bioengineering (L J Mullins, Ed.), pp. 157-180.

[22] J Wolpaw, D McFarland, G Neat, C Forneris (1991), An EEG-Based Brain-Computer Interface for Cursor Control, Electroencephalography and Clinical Neurophysiology, 78, 3, pp. 252-9.

[23] H Berger (1969), On the Electroencephalogram of Man, The Fourteen Original Reports on the Human Electroencephalogram ,Electroencephalography and Clinical Neurophysiology, Supplement No. 28. Elsevier, Amsterdam.

[24] G Dornhege, J R Millan, T Hinterberger, D J McFarland and K-R Muller (Eds.), Toward Brain-Computer Interfacing, The MIT Press, Cambridge, MA.

[25] E R Miranda (2006), Brain-Computer Interface for Generative Music, Proc. of International Conference Series on Disability, Virtual Reality and Associated Technologies (ICDVRAT 2006), Esbjerg, pp. 295-302.

[26] K E Misulis (1997), Essentials of Clinical Neurophysiology, Butterworth-Heinemann, Boston, MA.

[27] E Niedermeyer and F H L da Silva (Eds.), Electroencephalography, 2nd edition. Urban and Schwartzenberg, Munich

[28] Steven G. Mason, Member, IEEE and Gary E. Birch, Member, IEEE, “A General Framework for Brain- Computer Interface Design” , VOL. 11, NO. 1, MARCH 2003

[29] Michael J. Riezenman, “Melding Mind and Machine”- IEEE publications, issue June 2008

[30] Janne Lehtonen, “EEG-based Brain Computer Interfaces”, May 2002

[31] Pasi Jylänki, “Classification of single-trial EEG for online brain-computer interface”, June 2006

[32] Jessica D. Bayliss, “A Flexible Brain-Computer Interface”, University of Rochester, 2001

[33] J. Kalcher, D. Flotzinger, C. Neuper, S. Gölly, and G. Pfurtscheller, "Graz Brain-Computer Interface II: towards communication between humans and computers based on online classification of three different EEG patterns," Med. Biol. Eng. Comput., vol. 34, pp. 382- 388, 1996.

[34] J.J. Vidal, "Toward direct brain-computer communication," Annu. Rev. of Biophys. Bioeng., pp. 157-180, 1973.

[35] J.R. Wolpaw and D.J. McFarland, "Multichannel EEG-based brain-computer communication," Electroenceph. Clin. Neurophysiol., vol. 90, pp. 444-449, 1994.

[36] E. Sutter, "The brain response interface: communication through visually-induced electrical brain response," J. Microcomput. Applications, vol. 15, pp. 31-45, 1992.

[37] A. Kübler, B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. Perelmouter, M. Schauer, C. Fritsch, E. Taub, and N. Birbaumer, "Thought Translation Device: A Neurophysiological Approach to Communication in Total Motor Paralysis," Exp. Brain Research, vol. 124, pp. 223-232, 1999.

[38] G. Pfurtscheller, J. Kalcher, C. Neuper, D. Flotzinger, and M. Pregenzer, "On-line EEG classification during externally-paced hand movements using a neural network-based classifier," Electroenceph. Clin. Neurophysiol., vol. 99, pp. 416-425, 1996.

[39] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor, “A spelling device for the paralysed,” Nature, vol. 398, pp. 297- 298, 1999

[40] D.B. Popovic, R.B. Stein, K.L. Jovanovic, R. Dai, A. Kostov, and W.W. Armstrong, "Sensory nerve recording for closed-loop control to restore motor functions," IEEE Biomed. Eng., vol. 40(10), pp. 1024-1031, 1993.

[41] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer, "EEG-based discrimination between imagination of right and left hand movement," Electroenceph. Clin. Neurophysiol., vol. 103, pp. 642-651, 1997.

[42] G. Pfurtscheller and C. Neuper, "Motor imagery activates primary sensorimotor area in humans," Neurosci. Lett., vol. 239, pp. 65-68, 1997.

[43] J. Müller-Gerking, G. Pfurtscheller, and H. Flyvbjerg, "Designing optimal spatial filters forsingle-trial EEG classification in a movement task," Electroenceph. Clin. Neurophysiol., vol. 110, pp. 787-798, 1999.

[44] D.J. McFarland, A.T. Lefkowicz, and J.R. Wolpaw, "Design and operation of an EEG-based brain-computer interface (BCI) with digital signal processing technology," Behav. Res. Meth. Instr. Comput., vol. 29, pp. 337-345, 1997.

[45] A. Schlögl, D. Flotzinger, and G. Pfurtscheller, "Adaptive autoregressive modeling used for single-trial EEG classification," Biomed. Technik, vol. 42, pp. 162-167, 1997.

[46] D.Flotzinger, J. Kalcher, and G. Pfurtscheller, "EEG classification by learning vector quantization," Biomed. Technik, vol. 37, pp. 303-309, 1992.

[47] K. Lugger, D. Flotzinger, A. Schlögl, M. Pregenzer, and G. Pfurtscheller, "Feature extraction for on-line EEG classification using principal components and linear discriminants," Med. Biol. Eng. Comput., vol. 36, pp. 309-314, 1998.

[48] G. Pfurtscheller, C. Neuper, A. Schlögl, and K. Lugger, "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters," IEEE Trans. Rehab. Engng., vol. 6, pp. 316-325, 1998.

[49] Neuper, A. Schlögl, and G. Pfurtscheller, "Enhancement of left-right sensorimotor EEG differences during feedback-regulated motor imagery," J. Clin. Neurophysiol., vol. 16(2),

1999

[50] Guger, A. Schlögl, D. Walterspacher, and G. Pfurtscheller, "Design of an EEG-based brain computer interface (BCI) from standard components running in real-time under Windows," Biomed. Technik, vol. 44, pp. 12-16, 1999

[51] C.Guger, "Implementation of different EEG processing algorithms with S-Functions," Master thesis, University of Technology Graz, 1997.

[52] S. Haykin, Adaptive Filter Theory. New Jersey: Prentice Hall, Englewood Cliffs, 1986.

[53] B. Hjorth, "EEG analysis based on time domain properties," Electroenceph. Clin. Neurophysiol., vol. 29, pp. 306-310, 1970.

[54] T.M. Vaughan, J.R. Wolpaw, and E. Donchin, "EEG-based communication: Prospects and problems," IEEE Trans. Rehab. Engng., vol. 4, pp. 425-430, 1996.