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Music Neurotechnology: a natural progression

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Abstract

Music has always had a connection with science, which is facilitated by the latest technologies of the time. The 16th century luthier's *savoir faire* to manufacture violins and the plethora of software available these days to compose and analyse music with sophisticated modelling and statistical methods, are only two examples of this. This chapter examines how this connection is progressing nowadays, in particular with relation to musical creativity and Biology. The term 'Music Neurotechnology' appeared for the first time in *Computer Music Journal* in 2009, to refer to a new research area that is emerging at the crossroads of neurobiology, engineering sciences and music. After a brief introduction to Music Neurotechnology, the chapter discusses the authors' own projects in this field, including the development of a technique to synthesise sounds representing the behaviour of neurones cultured *in vitro* and the composition of orchestral music using rhythms generated by computer simulations of brain tissue. Research into brain-computer music interface (BCMI) is introduced as an example of the potential impact of Music Neurotechnology to biomedical engineering in addition to musical creativity. The conclusion suggests that Music Neurotechnology holds a tremendous potential to harness the benefits of music to society and human development.

1. INTRODUCTION

Imagine if you could play a musical instrument with signals detected directly from your brain. Would it be possible to generate music representing brain activity? What would the music of our brains sound like? These are some of the questions addressed by our research into Music Neurotechnology[1], a new field of research that is emerging at the crossroads of neurobiology, engineering sciences and music. Systems that interact directly with our nervous system (Rosenboom 2003), sonification methods to diagnose brain disorders (Vialatte et al. 2012) and bio-computing devices (Braund and Miranda 2015) are emerging plausible technologies for musical creativity, which 100 years ago were thinkable perhaps only in the realm of science fiction.

Many recent advances in the neurosciences, especially in Computational Neuroscience, have led to a deeper understanding of the behaviour of individual and large groups of biological neurones and we can now begin to apply biologically informed neuronal functional paradigms to problems of design and control, including applications pertaining to music technology and creativity. For instance, we have been exploring the behaviour of computational models of brain functioning to make music with. We find their ability to generate very complex biological-like behaviour from the specification of relatively simple parametric variables compelling and inspiring. They allow for the design of complex sound generators and sequencers controlled by a handful of parameters. We have been looking into designing new musical instruments based on such models.

Moreover, a better understanding of the brain combined with the emergence of increasingly sophisticated devices for scanning the brain is enabling the development

[1] The term 'Music Neurotechnology' appeared in print for the first time in 2009 in the editorial of *Computer Music Journal*, volume 33, number 1, page 1.

of musical interfaces with our neuronal systems. These interfaces have tremendous potential to enable access to active music making to people with severe physical impairments, such as severe paralysis after a severe stroke or accident damaging the spinal cord, in addition to open the doors to completely new ways to harness creative practices.

This chapter discusses four projects that epitomize the research that we have been conducting it the field of Music Neurotechnology at Plymouth University's Interdisciplinary Centre for Computer Music Research (ICCMR)[2]. The first looks into harnessing the behaviour of neuronal tissue cultured *in vitro*, with a long-term ambition to build hybrid bio-silicon musical processors. The second project concerns developing methods to compose music inspired and informed by neurobiology, more specifically we introduce *Shockwaves*, a violin concertino whose first half was composed using rhythms generated with a simulated neuronal network. Then, we introduce our work into developing brain-computer music interfacing (BCMI) technology and present two projects, one aimed at enabling people with physical disabilities to make music and another which explored the potential of BCMI technology for creative musical composition and performance more generally.

2. SOUND SYNTHESIS WITH *IN VITRO* NEURONAL NETWORKS

Computational paradigms informed by the principles of information processing in physical, chemical and biological systems are promising new venues for the development of new types of intelligent machines. There has been a growing interest in research into the development of neurochips coupling living brain cells and silicon circuits together. The ambition here is to harness the intricate dynamics of *in vitro* neuronal networks to perform computations.

A number of researchers have been looking in to developing ways to culture brain cells in mini Petri-like dishes measuring only a few square millimetres. These devices are referred to as MEA (short for Multi-Electrode Array) devices. They are embedded with electrodes that detect the electrical activity of aggregates of cells and stimulate them with electrical pulses. It has been observed that in vitro cultures of brain cells spontaneously branch out, even if they are left to themselves without external input. They have a strong disposition to form synapses, even more so if subjected to electrical stimulation (Potter et al. 2006).

Research into hybrid wetware-silicon devices with *in vitro* neuronal networks has been making continual progress. DeMarse et al. (2001) reported the pioneering development of a neuronally-controlled artificial animal - or Animat - using

[2] Created in 2003, ICCMR develops musical research and provides post-graduate training at the crossroads of art and science. Originally based at the former School of Computing, ICCMR is now affiliated to the university's Arts Institute. Its research expertise ranges from musicology and composition to biomedical applications of music and development of new music technologies. Website: http://cmr.soc.plymouth.ac.uk/

dissociated cortical neurones from rats cultured on a MEA device. Distributed patterns of neuronal activity, also referred to as spike trains, controlled the behaviour of the Animat in a computer-simulated virtual environment. The Animat provided electrical feedback about its movement within its virtual environment to the cells on the MEA device. Changes in the Animat's behaviour were studied together with the neuronal processes that produced those changes in an attempt to understand how information was encoded and processed by the cultured neurones. Potter et al. (2004) described a similar study, but they have used physical robots instead of simulated Animats. In this case, different patterns of spike trains triggered specific robotic movements; e.g., step forward, turn right, and so on. The robot was fitted with light sensors and returned brightness information to the MEA as it got closer to the light source. The researchers monitored the activity of the neurones for new signals and emerging neuronal connections.

We are interested in developing interactive musical computers based on such neurochips. As an entry point to kick-start our research towards this end, the BioMusic team at ICCMR teamed up with scientists at University of the West of England (UWE), Bristol, to look into developing methods for rendering the temporal behaviour of *in vitro* neuronal networks into sound (Miranda et al. 2009). The dynamics of *in vitro* neuronal networks represent a source of rich temporal behaviour, which inspired us to develop and test a number of rendering methods using different sound synthesis techniques, one of which will be introduced below.

The UWE team developed a method to extract brain cell from hen embryos at day seven *in ovo* and maintain them for relatively long periods of time, typically several months (Uroukov et al. 2006). Figure 1 shows a typical hen embryo aggregate neuronal culture, also referred to as a *spheroid*. In our experiments, spheroids were grown in culture in an incubator for 21 days. Then, they were placed into a MEA device in such a way that at least two electrodes made connections into the neuronal network inside the spheroid. One electrode was designated as the input by which we applied electrical stimulation and the other as the output from which we recorded the effects of the stimulation on the spheroid's spiking behaviour. The appropriateness of a connection is ascertained through the recording of the constant spontaneous spiking activity within the spheroid on a given electrode (Uroukov et al. 2006).

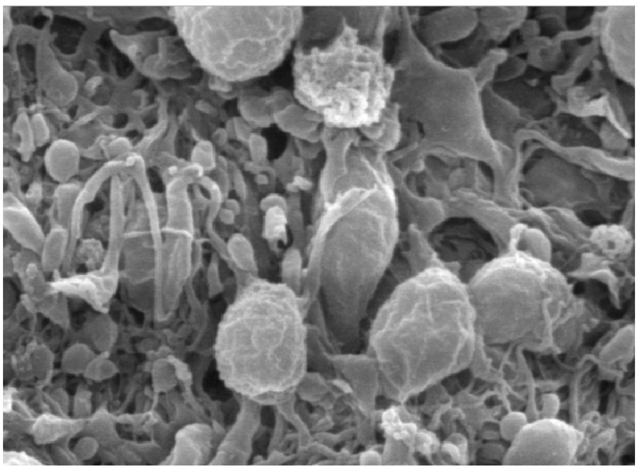

Figure 1: Image of a typical hen embryo aggregate neuronal culture on a scanning electron microscope, magnified 2,000 times. (Courtesy of Larry Bull, University of

the West of England, UK.)

Electrical stimulation at the input electrode consisted of a train of biphasic pulses of 300mv each, coming once every 300ms. This induced change in the stream of spikes at the output electrode, which was recorded and saved into a file[3].

The resulting neuronal activity for each session was saved on separate files. Figure 2 plots an excerpt lasting for 1 second of typical neuronal activity from one of the sessions. Note that the neuronal network is constantly firing spontaneously. The noticeable spikes of higher amplitude indicate concerted increases of firing activity by groups of neurones in response to input stimuli.

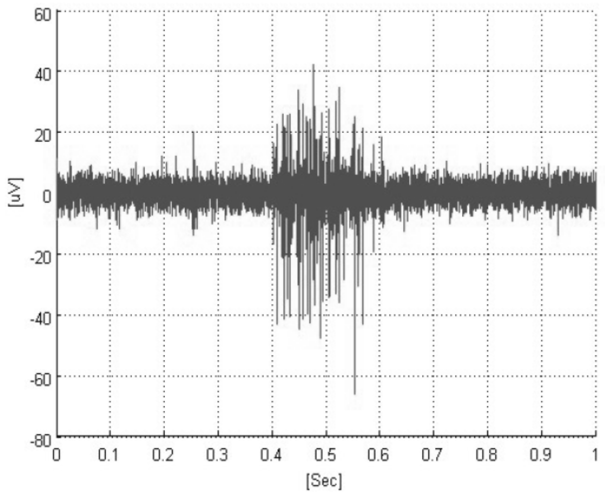

Figure 2: Plotting of the first second of a data file showing the activity of the spheroid in terms of μV against time. Induced spikes of higher amplitudes took place between 400ms and 600ms.

We developed and tested a number of methods to sonify the activity of the neuronal network using different synthesis techniques, including FM, AM, subtractive synthesis, additive synthesis and granular synthesis. Here we introduce a method that combined aspects of granular synthesis and additive synthesis.

We implemented an additive synthesiser (Miranda 2002) with nine sinusoidal oscillators, which required three input values to generate a tone: frequency (*freq*), amplitude (*amp*) and duration (*dur*). We established that the neuronal data would produce *freq* and *amp* values for the first oscillator only. Then the values for the other oscillators were calculated relative to the values of the first oscillator; e.g., $freq_{osc2} = freq_{osc1} \times 0.7$, $freq_{osc3} = freq_{osc1} \times 0.6$, and so on. The synthesiser was implemented in Csound and we wrote an application in C++ to generate the respective Csound score files from the data files.

[3] The reader is invited to consult (Miranda et al. 2009) for more information about the stimulation and observed behaviour of the network.

Initially, we synthesised a tone for every datum. However, this produced excessively long sounds. In order to address this problem, a data compression technique was developed, which preserved the data behaviour that we were interested to sonify, namely patterns of neuronal activity and induced spikes. For clarity, we firstly describe the method whereby we produced a tone for every datum. Then we present the method using data compression. We experimented with a number of values on an ad hoc basis and made choices intuitively based on the results obtained; there were no specific a priori criteria.

In the case of synthesis of one tone per datum, each datum yielded three values for the synthesiser: frequency (*freq*), amplitude (*amp*) and duration (*dur*). The frequency value is calculated in Hz as follows: $freq = (datum \times 20) + \alpha$. We set $\alpha = 440$ as an arbitrary reference to 440Hz; changes to this value produce sonifications at different registers.

The synthesiser's amplitude parameter is a number between 0 and 10. The amplitude is calculated as follows: $amp = 2 \times \log_{10}(abs(datum) + 0.01) + 4.5$. This produces a value between 0.5 and 9.5. In order to avoid negative amplitudes we take the absolute value of the datum. Then, 0.01 is added in order to avoid the case of logarithm of 0, which cannot be computed. We later decided to multiply the result of the logarithm by 2, in order to increase the interval between the amplitudes. Since $\log_{10}(0.01) = -2$, if we multiply this result by 2 then the minimum possible outcome would be equal to -4. We add 4.5 to the result because our aim is to assign a positive amplitude value to every datum, even if it values 0μV.

The duration of the sound is calculated in secs; it is proportional to the absolute value of the datum, which is divided by a constant *c*, as follows:

$$dur = \frac{abs(datum)}{c} + t$$

In the case of the present example *c* was set equal to 100. The higher the value of *c*, the more "granular-like" the results. We add *t* to the result in order to account for excessively short or possibly null durations (e.g., $t = 0.05$).

The compression algorithm was implemented as follows: it begins by creating a set with the value of a datum. To start with, this will be the first sample of the data. Then it feeds in the second sample, the third, and so on. The value of each incoming sample is compared with the value of the first sample in order to check if they are close to each other according to a given distance threshold Δ. If the difference between them is lower than Δ, then the incoming datum is stored in the set. Otherwise, the values of all data stored in the set are averaged and used to generate a tone; this provided an efficient way to compress the data while preserving its overall behaviour. Then, a new set is created, whose first value is the value of the datum that prompted the creation of the last tone, and so forth. In this case, the frequency of a tone is calculated as follows, where *n* is the minimum value found in the data file that is being sonified and *x* is the maximum value:

$$freq = \left(\frac{(set\_average - n) \times 900}{x - n} \right) + 100$$

In the equation above, the values of n and x do not necessarily need to be the minimum and maximum values in the data file; they can be set arbitrarily, with the condition that $n < x$. The result is scaled in order to fall in the range between 100Hz and 1kHz. The amplitude is calculated as for the case of one tone per datum, as described above, with the only difference that the *datum* is replaced by the *set average*. The duration is also calculated as described above with the difference that we introduce a bandwidth defined by minimum and maximum duration thresholds. If the calculated duration of a tone falls outside the bandwidth, then the system assigns a predetermined duration value; e.g., the tone is assigned a duration of 0.1s if its calculated duration is below the minimum threshold.

Figure 3 shows the cochleogram of an excerpt of a sonification, where one can clearly observe sonic activity corresponding to induced spiking activity.

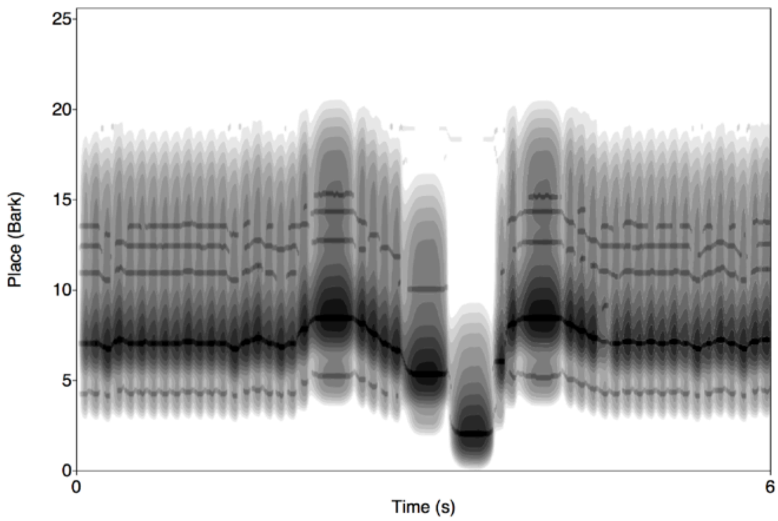

Figure 3: Cochleogram of an excerpt of a sonification where spikes of higher amplitude can be visually seen just after the middle of the diagram.

3. RHYTHMS OF SPIKING NEURONS

Obviously, more work is needed in order to establish how owe might be able to exert controllability and repeatability in systems based on *in vitro* neuronal networks. However, basic experiments such as the one introduced above are useful because they often lead to ideas that we would not have had otherwise. For instance, during our sonification experiments we were amazed by the variety of rhythmic patterns produced by the neurones, which gave us the idea of generating rhythms for a piece of music using a model of a spiking neuronal network.

We teamed up with Etienne B. Roesch, a cognitive scientist at the University of Reading, to implement a computer model of a network of spiking neurones. As with the aforementioned experiments with *in vitro* neurones, when the network model is stimulated with an external signal, the neurones of the network produce bursts of activity, forming streams of rhythmic patterns. The advantages of working with a computer model are that we can set its parameters to produce different behaviours in a highly controlled manner and can trace the spiking activity of each individual neurone on a *raster plot*, which is a graph plotting the spikes.

In this section we will introduce a method we developed to compose music based on such raster plots and *Shockwaves*[4], Eduardo Miranda's violin concertino for orchestra, percussion and electronics. One of the musical ideas that the composer wanted to convey in this composition is the notion of a rhythmic structure that would emerge from widely dispersed events in the time line. These somewhat pointillist events would become increasingly frequent and complex as the piece evolved, which would then lead to regular rhythm resembling a samba school. This is the form of the first half of the concertino and was composed entirely with raster plots.

In a nutshell, the composer orchestrated raster plots by allocating each instrument of the orchestra to a different neurone of the network simulation. Each time a neurone produced a spike, its respective instrument was prompted to play a certain note. The actual pitches for the notes were assigned based upon a series of chords, which served as a framework to make simultaneous spikes sound in harmony.

Our implementation is based on model that simulates the spiking behaviour of biological neurones, developed by computational neuroscientist Eugene Izhikevich. A biological neurone aggregates the electrical activity of its surroundings over time, until it reaches a given threshold. At this point it generates a sudden burst of electricity, or spike, referred to as an *action potential*. The model has a number of parameters, which define how the neurones behave; for instance, one of the parameters defines the spiking threshold, or sensitivity of the neurones to release an action potential[5].

As we ran the model, each action potential produced by a neurone was registered and transmitted to other neurones, producing waves of activation, which spread over the entire network. A raster plot showing an example of such collective spiking behaviour, taken from a simulation of a network of 50 neurones, is shown in Figure 4. This results from a simulation of the activity of this group of 50 artificial neurones over a period of 10 seconds: the neurones are numbered on the y-axis (with neurone number 1 at the bottom, and neurone number 50 at the top) and time, which runs from zero to 10,000 milliseconds, is on the x-axis. Every time one such neurone spikes, a dot is placed on the graph at the respective time.

[4] *Shockwaves* was premiered on 20 June 2015, in The House, Plymouth, by Ten Tors Orchestra under the baton of Simon Ible, with Pierre-Emmanuel Largeron on the solo violin. A recording is available on SoundCloud: https://soundcloud.com/ed_miranda/shockwaves

[5] A detailed explanation of the model is beyond the scope of this chapter; please refer to (Izhikevich 2007) for more information.

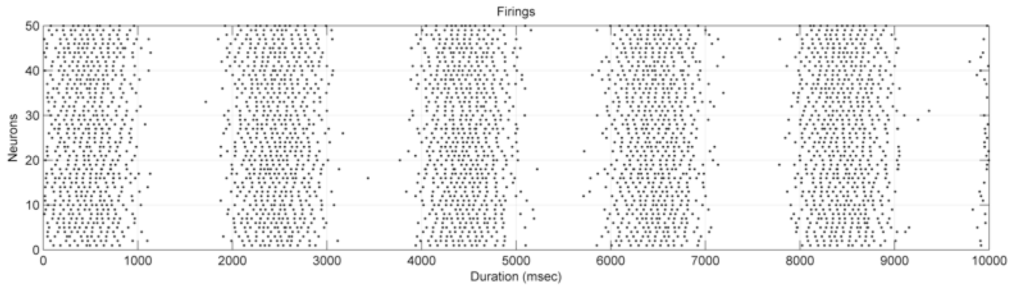

Figure 4: A raster plot illustrating collective firing behaviour of a simulated network of spiking neurones. Neurone numbers are plotted (y-axis) against time (x-axis) for a simulation of 50 neurones over a period of 10 seconds. Each dot represents a spiking event.

Figure 4 shows periods of intense collective spiking activity separated by quieter moments. These moments of relative quietness in the network are due to the refractory period during which neurones that have spiked remain silent as their electrical potentials decay back to a baseline value[6]. Of course, the network needs to be stimulated to produce such patterns of activation.

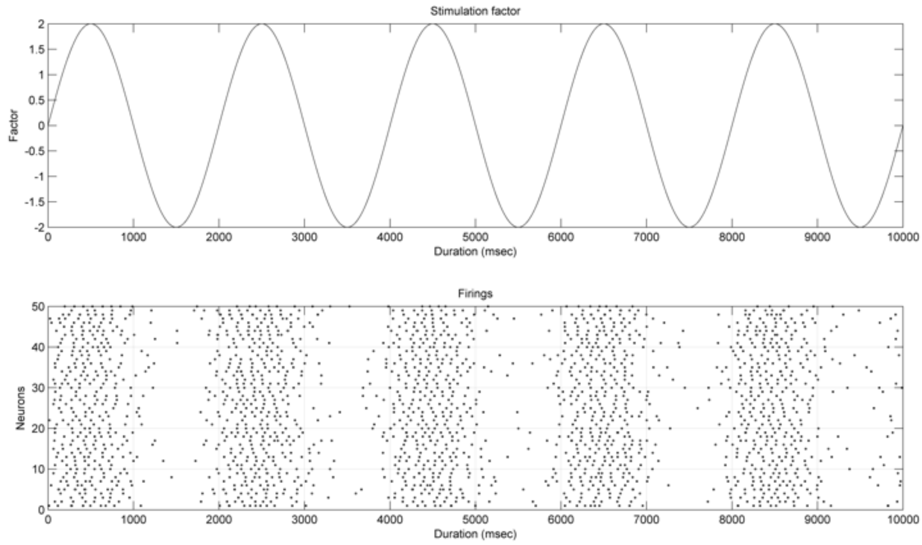

Figure 5: At the top is a sinusoid signal that stimulated the network that produced the spiking activity represented by the raster plot at the bottom.

For the composition of *Shockwaves*, the network was stimulated with a sinusoidal signal that was input to all neurones of the network simultaneously. Generally speaking, the amplitude of this signal controlled the overall intensity of firing through the network. For instance, the bottom of Figure 5 shows a raster plot generated by a

[6] The action of the so-called 'inhibitory' neurons in the model is also a contributing factor here.

network of 50 spiking neurones stimulated by the sinusoid shown at the top of the figure. As the undulating line rises, the spiking activity is intensified[7].

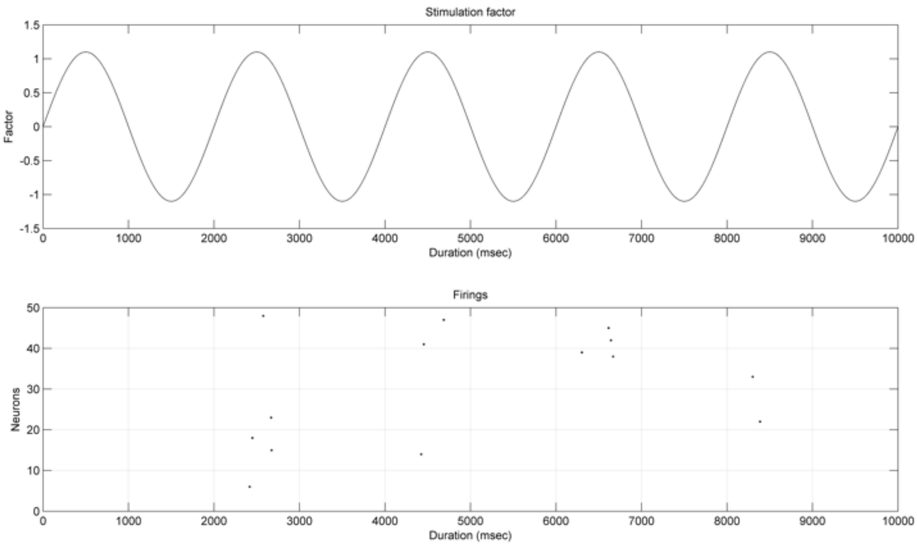

Figure 6: An example of a run of the simulation that produced sparse spiking activity because the amplitude of the sinewave and the spiking sensitivity of the neurones were set relatively low.

In order to compose *Shockwaves*, the network was set up with 50 neurones and the simulation was run several times, lasting for 10 seconds each. For all runs of the simulation the stimulating sinusoid was set to a frequency of 0.0005 Hz, which means that each cycle of the wave lasted for 2 seconds. Therefore, each simulation took five cycles of the wave, which can be seen at the top of Figures 5 and 6, respectively.

The amplitude of the sinusoid and the sensitivity of the neurones to fire varied for each run of the simulation. The amplitude of the model's stimulating signal could be varied from 0.0 (no power at all) to 5.0 (maximum power) and the sensitivity of the neurones could be varied from 0.0 (no sensitivity at all; would never fire) to 5.0 (very sensitive). For instance, for one of the first runs of the simulation the power of the stimulus was set to 1.10 and sensitivity of the neurones to 2.0 (Figure 6), whereas in a late run these were set to 2.0 and 4.4, respectively (Figure 5). One can see that the higher the power of the stimulus and the higher the sensitivity, the more likely the neurones are to fire and therefore the more spikes the network produces overall.

The composer established that each cycle of the stimulating sinusoid would produce spiking data for three measures of music (with time signature equal to 4/4). This was established intuitively, after experimenting with the density of spiking activity produced with a range of different amplitudes for the sinusoid. More than three

[7] Note that a more complex signal could replace the sinusoid; for instance, a sound other than a sinusoid could be used to simulate the network. In this case, the raster plots would look much more complex than the ones shown in this chapter.

measures would produce too many notes at maximum sinusoid amplitude (i.e., high density of spikes) and less than three measures would produce excessively long periods of silence at lower amplitudes (i.e., very few spikes). In order to transcribe the spikes as musical notes he decided to adjust them to fit a metric of semiquavers. Then, he associated each instrument of the orchestra to a neurone, as shown in Table 1. As the orchestra comprised 33 instruments, only the first 33, counting from the bottom of the raster plots upwards, were used[8].

Neurone	**Instrument**	**Neurone**	**Instrument**
1	Contrabass	18	Solo violin
2	Cello 3	19	Snare drum
3	Cello 2	20	Maracas
4	Cello 1	21	Bass Drum
5	Viola 3	22	Cymbal
6	Viola 2	23	Wood Blocks
7	Viola 1	24	Tubular Bells
8	2nd Violin 4	25	Timpani
9	2nd Violin 3	26	Trumpet 2
10	2nd Violin 2	27	Trumpet 1
11	2nd Violin 1	28	Horn 2
12	1st Violin 6	29	Horn 1
13	1st Violin 5	30	Bassoon 2
14	1st Violin 4	31	Bassoon 1
15	1st Violin 3	32	Oboe 2
16	1st Violin 2	33	Oboe 1
17	1st Violin 1	34	Flute

Table 1: Instruments are associated to neurones of the network. Each instrument plays the spikes produced by its respective neurone.

The compositional process progressed through three major steps: the establishment of a rhythmic template, the assignment of pitches to the template and the articulation of the musical material.

[8] Initially, the composition was planned for an orchestra of 50 instruments, but due to unforeseen circumstances the commission ended up being for an ensemble of 33 instruments.

Figure 7: Transcribing spikes from a raster plot as semiquavers on a score.

In order to establish the rhythmic template, firstly the composer transcribed the spikes as semiquavers onto the score. Figure 7 shows an excerpt of the result of this transcription for a section of the strings. The spikes were converted into musical notes manually. The raster plots for each cycle of the stimulating signal were printed and enlarged on a photocopier. Then, a template drawn on an acetate sheet was placed on top of each print to establish the positions of the spikes and transcribe them into musical notation (Figure 8).

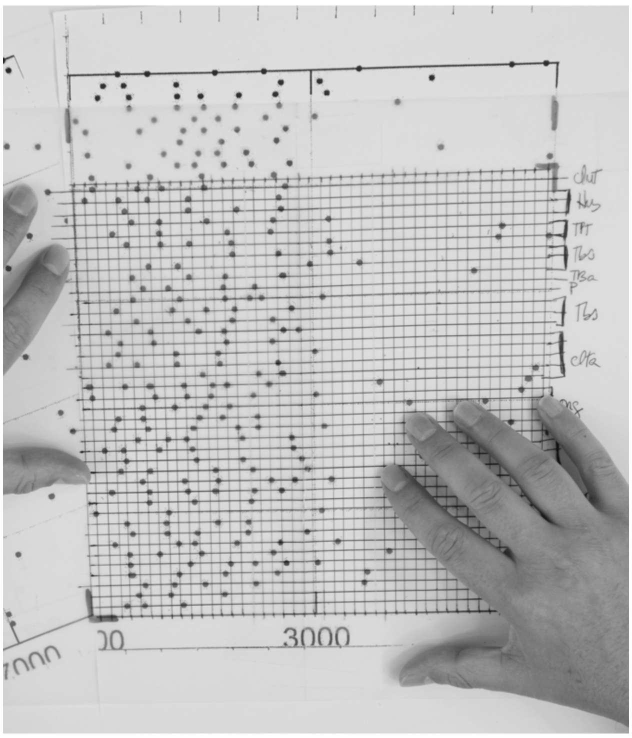

Figure 8: The process of converting the spikes into musical notes was done manually.

In order to forge more musically plausible rhythmic figures, the durations of the notes and rests were altered slightly, while preserving the original spiking pattern. Figure 9 shows the new version of the score shown in Figure 7 after this process. Figure 10 shows the final result of the compositional process, with pitches and articulation.

Figure 9: Resulting rhythmic template.

Figure 10: The resulting musical passage.

As mentioned earlier, the notes for the rhythmic template (Figure 9) were assigned based on a chord progression. Pitches were assigned differently as the piece progressed; for instance, sometimes a chord provided pitches for a beat of the 4/4 measure, but some other times a single chord provided pitches through various measures. In general those figures to be played by instruments of lower tessitura were assigned the lower pitches of the chords and those to be played by instruments of higher tessitura were assigned the higher pitches, and so on. There were occasions where pitches were transposed one octave upwards or downwards in order to best fit specific contexts or technical constraints of the various instruments. Other adjustments also occurred during the process of articulating the musical materials; for example, pitches might have been changed in order to render a specific passage more idiomatic for the respective instrument and/or forge smoother voice leading.

4. BRAIN-COMPUTER MUSIC INTERFACING

Brain-computer interfacing technology, or BCI, allows a person to control devices by means of commands expressed by brain signals, which are detected through brain monitoring technology (Dornhege et al. 2007). We are interested in developing brain-computer interfacing technology for music, or BCMI[9], aimed at people with special needs and music therapy, in particular for people with severe physical disability who have relatively preserved cognitive functions. Severe brain injury, spinal cord injury and locked-in syndrome result in weak, minimal or no active movement, which therefore prevent the use of gesture-based devices. These patient groups are currently either excluded from music recreation and therapy, or are left to engage in a less active manner through listening/receptive methods only (Miranda et al. 2011).

Currently, the most viable and practical method of detecting brain signals for BCMI is through the electroencephalogram, abbreviated as EEG[10], recorded with electrodes placed on the scalp. The EEG expresses the overall electrical activity of millions of neurones, but it is a difficult signal to handle because it is extremely faint, and it is filtered by the membranes that separate the cortex from the skull (meninges), the skull itself and the scalp. This signal needs to be amplified significantly and harnessed through signal processing techniques in order to be used in a BCI or a BCMI (Miranda 2010).

In general, power spectrum analysis is the most commonly used method to analyse the EEG signal[11]. In simple terms, power spectrum analysis (Fast Fourier Transform, or FFT) breaks the EEG signal into different frequency bands and reveals the distribution of power between them. This is useful because it is believed that specific distributions of power in the spectrum of the EEG can encode different cognitive behaviours (Miranda and Caster 2014).

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[9] The expression Brain-Computer Music Interfacing, or BCMI, was coined by the ICCMR team to denote BCI systems for musical applications and it has been generally adopted by the research community.

[10] The EEG is a measurement of brainwaves detected using electrodes placed on the scalp. It is measured as the voltage difference between two or more electrodes on the surface of the scalp, one of which is taken as a reference. Other methods for measuring brain activity include MEG (magnetoencephalography), PET (positron emission tomography) and fMRI (functional magnetic resonance imaging), but they are not practical for BCI.

[11] Please refer to (Miranda and Castet 2014) for an overview of EEG analysis methods.

As far as BCI systems are concerned, the most important frequency activity in the EEG spectrum lies below 40Hz. There are five, possibly six, recognised bands of EEG activity below 40Hz, also referred to as EEG rhythms, which are often associated with specific states of mind. For instance, the frequencies falling between 8Hz and 13Hz are referred to as alpha rhythms and are usually associated with a state of relaxed wakefulness; e.g., as in a state of meditation. The exact boundaries of these bands are not so clearly defined and the meaning of these associations can be contentious. In practice, however, the exact meaning of EEG rhythms is not so crucial for a BCI system. What is crucial is to be able to establish whether or not users can produce power within distinct frequency bands voluntarily. For instance, alpha rhythms have been used to implement an early proof-of-concept BCMI system, which enabled a person to switch between two types of generative algorithms to produce music on a MIDI-controlled Disklavier piano in the style of Robert Schumann (when alpha rhythms were detected in the EEG) and Ludwig van Beethoven (when alpha rhythms were not detected) (Miranda 2006).

Broadly speaking, there are two approaches to steering the EEG for a BCI: conscious effort and operant conditioning. Conscious effort induces changes in the EEG by engaging in specific cognitive tasks designed to produce specific EEG activity (Miranda et al. 2004; Curran and Stokes 2003). The cognitive task that is most often used in this case is motor imagery because it is possible to detect changes in the EEG of a subject imagining the movement of a limb, such as a hand (Dornhege et al. 2007). Operant conditioning involves the presentation of a task in conjunction with some form of feedback, which allows the user to develop a somewhat unconscious control of the EEG (Kaplan et al. 2005). In between these two aforementioned approaches sits a paradigm referred to as evoked potentials.

Evoked potentials (EP) are spikes that appear in the EEG in response to external stimuli. EP can be evoked from auditory, visual or tactile stimuli producing auditory (AEP), visual (VEP) and somatosensory[12] (SSEP) evoked potentials, respectively. It is extremely difficult to detect the electrophysiological response to a single event in an on-going EEG stream. However, if the person is subjected to repeated stimulation at short intervals (e.g., 9 repetitions per second, or 9Hz) then the brain's response to each subsequent stimulus is evoked before the response to the prior stimulus has decayed. Thus, rather than being allowed to return to a baseline state, a so-called steady-state response can be detected.

Steady state visual evoked potential (SSVEP) is a robust paradigm for a BCI, on the condition that the user is not severely visually impaired. Typically, visual targets are presented to a user on a computer monitor representing tasks to be performed. These could be spelling words from an alphabet or selecting directions for a wheelchair to

[12] Our somatosensory system informs us about objects in our external environment through touch and about the position and movement of our body parts (proprioception) through the stimulation of muscle and joints. The somatosensory systems also monitor the temperature of the body, external objects and environment, and provide information about painful, itchy and tickling stimuli. In the context of this chapter, it is concerned with visual stimuli.

move, and so on. Each target is encoded by a flashing visual pattern reversing at a unique frequency. In order to select a target, the user must simply direct their gaze at the flashing pattern corresponding to the action he or she would like to perform. As the user's spotlight of attention falls over a particular target, the frequency of the unique pattern reversal rate can be accurately detected in his or her EEG through spectral analysis. It is possible to classify not only a user's choice of target, but also the extent to which he or she is attending the target. This gives scope for SSVEP-based BCI systems where each target is not a simple binary switch but can represent an array of options depending on the user's level of attention.

Effectively, each target of a BCI-based SSVEP system can be implemented as a switch with a potentiometer. This immediately suggests a number of musical applications.

In 2011 we completed the implementation of our first SSVEP-based BCMI system, which we tested with a patient with locked-in syndrome at the Royal Hospital for Neuro-disability, in London.

The system comprised four targets, as shown on the computer screen in front of the patient in Figure 11. Each target image represents a different musical instrument and a sequence of notes (Figure 12). Each image flashes reversing its colour (in this case the colour was red) at different frequencies: 7Hz, 9Hz, 11Hz and 15Hz, respectively. Thus, for instance if the person gazes at the image flashing at 15Hz, then the system will activate the xylophone and will produce a melody using the sequence of 6 notes that was associated with this target; these notes are set beforehand, and the number of notes can be other than 6. The more the person attends to this icon, the more prominent is the magnitude of the brain's SSVEP response to this stimulus, and vice-versa. This produces a varying control signal, which is used to make the melody. Also, it provides a visual feedback to the user; the size of the icon increases or decreases as a function of this control signal. The melody is generated as follows: the sequence of 6 notes is stored in an array, whose index varies from 1 to 6. The amplitude of the SSVEP signal is normalized so that it can be used as an index sliding up and down through the array. As the signal varies, the corresponding index triggers the respective musical notes stored in the array (Figure 13).

Figure 11: A patient with locked-in syndrome testing the BCMI system.

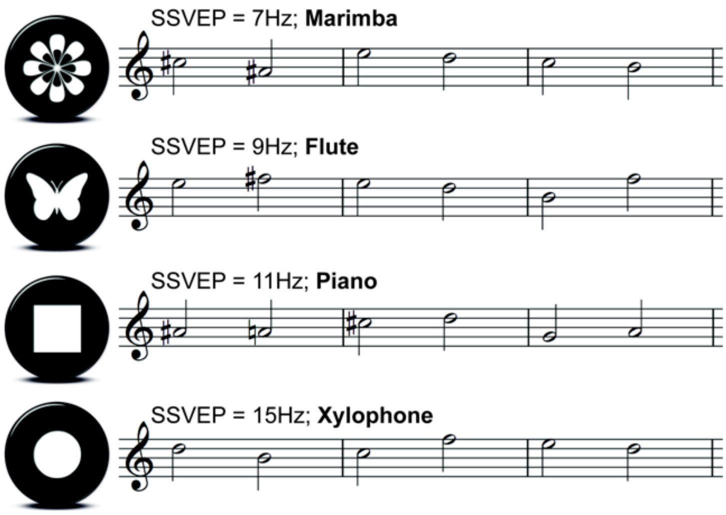

Figure 12: Each target image is associated with a musical instrument and a sequence of notes.

The system requires just three electrodes on the scalp of the user: a pair placed on the region of the visual cortex and a ground electrode placed on the front of the head. Filters were programmed to reduce interference of AC mains noise and artifacts such those generated by blinking eyes or moving facial muscles. SSVEP data was then filtered via band-pass filters to measure the band power across the frequencies correlating to the flashing stimuli.

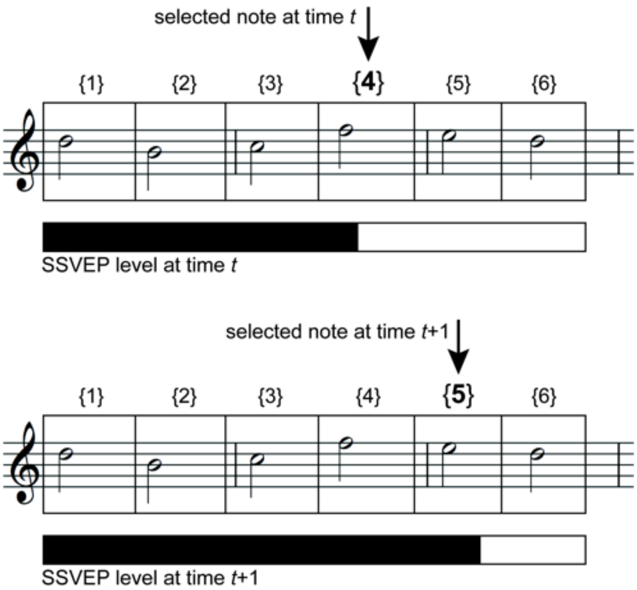

Figure 13: Notes are selected according to the level of the SSVEP signal.

The patient took approximately 15 minutes to learn how to use the system and she was able to quickly learn how to make melodies by increasing and decreasing the level of her SSVEP signal. We collected from the staff of the hospital and the patient suggestions and criticism with respect to improvements and potential further developments (Miranda et al. 2011). Two important challenges emerged from this exercise:

a) Everyone felt that the music sounded mechanical and it lacked expressivity because the system produced synthesised sounds. As far as the patients and the hospital's professionals were concerned, it would be preferable to make music with real acoustic musical instruments.

b) Our system enabled a one-to-one interaction with a musical system. However, it was immediately apparent that it would be desirable to design a system that would promote interaction amongst the participants. Therefore, our BCMI system should enable a group of participants to make music together.

4.1 *Activating Memory* and *The Paramusical Ensemble*

In order to address the abovementioned challenges, we adopted a slightly different research methodology. We started by dreaming a musical composition and a performance scenario first and then we considered how that would work in practice with our BCMI technology

In order to address the problem of lack of expressivity we came up with the idea that the patient would generate a score on the fly for a human musician to sight-read, instead of relaying it to a synthesiser. In order to promote group interaction we established that the composition would have to be generated collectively by a group of participants. However, the generative process would have to be simple and clearly understood by the participants. Also, the controlling-brain participants would need to clearly feel that they have control of what is happening with the music. Moreover, everyone involved would need to agree that the outcome sounds musical; whatever 'musical' means, it should be an enjoyable experience. Clearly, these were not trivial tasks. In the end, we established that the act of generating the music collectively and in real-time would have to be like playing a musical game, but with no winners or losers. We thought of designing something resembling a game of dominoes; that is, musical dominoes, played by sequencing blocks of pre-composed musical phrases selected from a pool. Finally, we created the concept of a musical ensemble where severely physically disabled and non-disabled musicians make music together: *The Paramusical Ensemble*. By way of related work, the concert of the British Paraorchestra[13] at the opening of the London Olympics Games in 2012 came to mind. However, the work introduced here addresses the development of bespoke technology and musical composition for a very specific type of impairment that is not tackled by the British Paraorchestra: brain-computer music interfacing for locked-in syndrome.

The result is Eduardo Miranda's *Activating Memory*, a piece for 8 participants, a string quartet and a BCMI quartet, and a new version of the SSVEP-based system. Each member of the BCMI quartet is furnished with the SSVEP-based BCMI system,

[13] http://www.paraorchestra.com/

which enables him or her to generate a musical score in real-time. Each of them generates a part for the string quartet, which is displayed on a computer screen for the respective string performer to sight-read during the performance (Figure 14).

Figure 14: A rehearsal of *The Paramusical Ensemble*, with locked-in syndrome patients performing *Activating Memory*.

The new BCMI system works similarly to the one described above, with the fundamental difference that the visual targets are associated with short musical phrases. Instead of flashing images on a computer monitor, we built a device with flashing LEDs and LCD screens to display what the LEDs represent (Figures 15 and 16). This new device increased the SSVEP response to the stimuli because it enabled us to produce more precise flashing rates than the ones we were able to produce using the standard computer monitors. Moreover, the LCD screens provided an efficient way to change the set of options available for selection. Subliminally, it promotes the notion that one is using a bespoke musical device to interact with others, rather interacting via a computer.

Figure 15: Photo of our new SSVEP stimuli device. In this photograph, the LCD screens are showing numbers, but in *Activating Memory* they display short musical phrases, such as the ones shown in Figure 16.

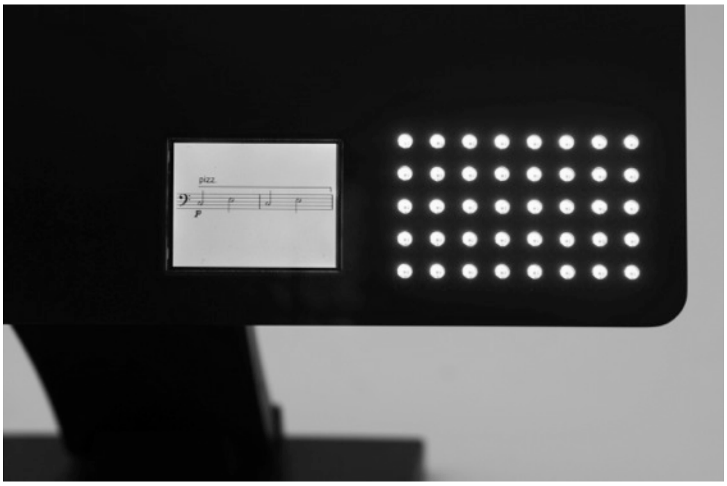

Figure 16: Detail from the SSVEP stimuli device, showing a short musical phrase displayed on the LDC screen.

Activating Memory is generated on the fly by sequencing 4 voices of predetermined musical sections simultaneously. For each section, the system provides four choices of musical phrases, or riffs, for each part of the string quartet, which are selected by the BCMI quartet (Figure 17). The selected riffs for each instrument are relayed to the computer monitors facing the string quartet for sight-reading. While the string quartet is playing the riffs for a section, the system provides the BCMI quartet with another set of choices for the next section. Once the current section has been played, the chosen new riffs for each instrument are subsequently relayed to the musicians, and so on. In order to give enough time for the BCMI quartet to make choices, the musicians repeat the respective riffs four times. The system follows an internal metronome, which guarantees synchronization.

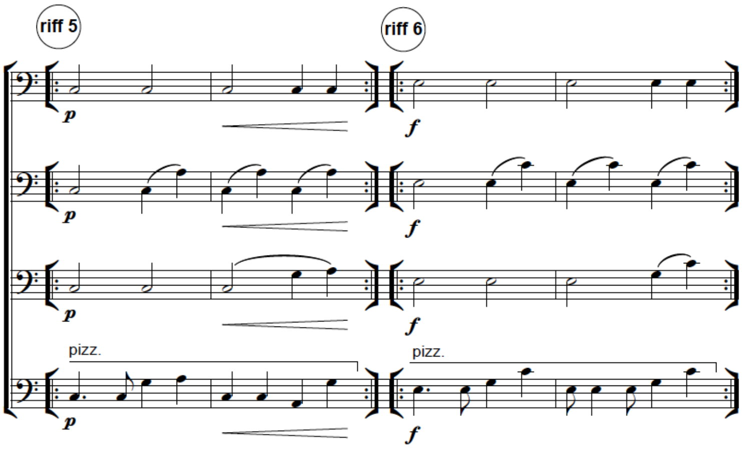

Figure 17: An example of two sets of four musical riffs on offer for two subsequent sections the violoncello part.

Activating Memory has been publicly performed on a number of occasions before we performed with *The Paramusical Ensemble*. This allowed us to make final adjustments to the system and music. *The Paramusical Ensemble*'s first public performance of *Activating Memory* took place on 17 July 2015 at the Royal Hospital for Neuro-disability in Putney, London[14].

4.2. *A Stark Mind*

A Stark Mind is a live audiovisual performance piece designed by Joel Eaton that expands the control on offer in *Activating Memory* by using a hybrid BCMI: an interface that combines more than one method of EEG detection. Designed for a hybrid BCMI performer and a trio of musicians playing violin, viola and percussion (Figure 18), the system provides the BCMI performer with a mix of conscious and unconscious control over multiple musical parameters at the same time. During a performance the BCMI performer's objective is to conduct the musicians by controlling a visual score. The score is projected onstage for both the audience to see and the musicians to sight-read.

Figure 18: Photo of musicians and hybrid BCMI performer (centre, rear) preparing to begin a performance of *A Stark Mind*. At the start of the performance the visual score is project on the back of the stage for the musicians, hybrid BCMI performer and the audience to see.

Unlike the traditional musical notation used in *Activating Memory* the score for *A Stark Mind* consists of colourful, abstract visual patterns. The decision for this was two-fold. Firstly, an abstract score allows for much more varied artistic interpretation, and although the graphics have direct musical connotations that are translated by the musicians, the option for musical variety is much wider, and this sense of freedom can help push the music in new directions, allowing the musicians to work together in novel ways making every performance different. Secondly, projecting the score onstage draws the audience in closer to the performance and allows them to see how

[14] A video documentary is available in Vimeo: https://vimeo.com/143363985
And a recording of one of the millions of possible renderings of *Activating Memory* is available on SoundCloud: https://soundcloud.com/ed_miranda/activating-memory

the hybrid BCMI performer's brainwaves are able to control the visual display and conduct the musicians at the same time, without having to be able to read musical notation.

The primary method of control in *A Stark Mind* is, again, the SSVEP technique. However, for this piece we have expanded the SSVEP control to allow 8 channels provided by combining two of our stimuli units. The SSVEP choices allow the hybrid BCMI performer to select visual patterns and effects that correspond to different musical phrases and instrumental playing techniques. In addition, there are two other methods of brainwave control in *A Stark Mind*. The SSVEP technique is considered to be an *active* method of user control because the user is able to choose which icon to select, therefore affective responses can be considered as a passive means of control, since the user cannot explicitly choose the outcome. Measuring emotional indicators, known as affective responses, in EEG offers a particularly interesting area for creative exploration especially when considering the role music plays in influencing the emotions of a listener (Schmitt and Trainor 2001). As such, emotional control for music making presents itself as a natural pairing due to the emotional associations inherent with music for many listeners. Levels of arousal and valence, two indicators of affect, are commonly detected from EEG measured in the frontal cortex area of the brain. Russell's 2-dimensional model of affect (Figure 19), provides a way of parameterising emotional responses to music in 2-dimensions (Russell, 1980). In the hybrid BCMI we take arousal as the measure of mental activation and valence, measured as the symmetry across the left and right hemispheres of the brain, as an indication of either a positive or negative engagement with the music.

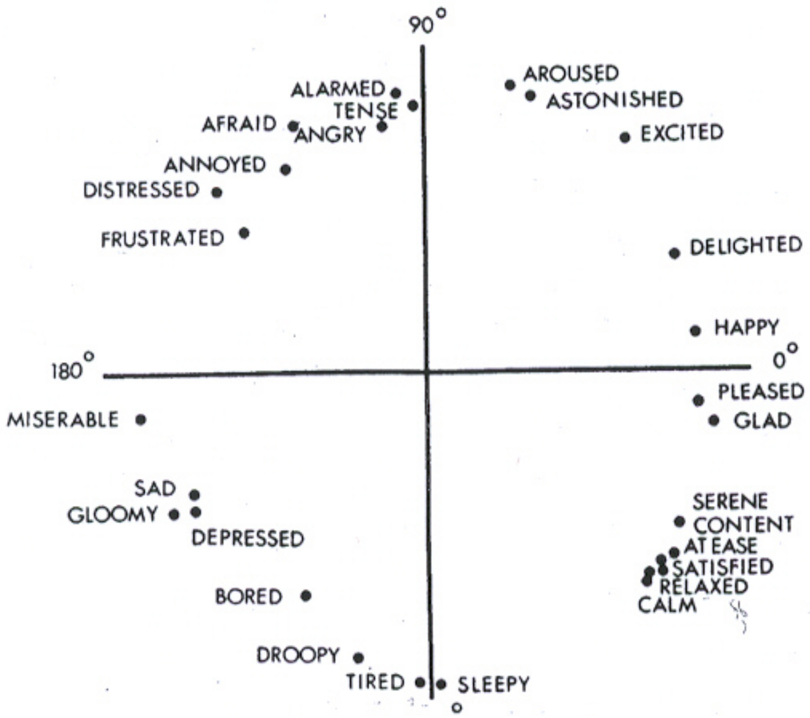

Figure 19: Russell's 2-dimensional model of affect illustrating emotions related to arousal (vertical axis) and valence (horizontal axis) (Russell, 1980).

During performances of *A Stark Mind* changes in valence and arousal are mapped to parameters of the visual score to invoke musical changes associated with different affective states. For example, if the hybrid BCMI performer's measure of arousal decreases during one time window of analysis indicating a move towards a state of 'calm', the playback speed of a particular visual pattern will increase by a corresponding amount. This conducts the musicians to play faster during the next time window. This increase in musical tempo has the knock-on effect of increasing the hybrid BCMI performer's arousal, which the system would target as 'excited', and so the mapping of arousal (and also of valence) is used to regulate the affective states of the hybrid BCMI performer during the performance by responding to their affective changes in real-time. This provides a novel approach to using emotional indicators in EEG to control music and also induce affective states in a manner that also adds an element of unpredictability and variance to the live performance.

In addition to SSVEP control and affective response a third, and another *active* method of control is incorporated into *A Stark Mind*. Motor imagery is a technique where a user imagines a specific physical movement. When programmed accordingly, the BCMI records the difference in brainwave patterns between imagining the movement and relaxation. This ability to detect distinctions in imaginations presents a particularly fascinating stage in the development of BCMI control as it is closely linked to reading thoughts by being able to distinguish mental actions. Sensorimotor rhythms are idle oscillatory waves that reduce in amplitude during motor imagery, providing a means of voluntary control. In the hybrid BCMI, motor imagery is measured by the detection of such amplitude reduction, known as event-related desynchronisation (ERD), in alpha rhythms across the motor cortex. In practice, if a user performs a motor imagery task such as imagining squeezing their right-hand, ERD is expected in the alpha band-power over the left motor cortex (note that the left motor cortex is contralateral to the right hand). The imagination of relaxed motor task has the opposite effect in increasing the alpha-band power back to the idle state (Daly, et al. 2014). In the hybrid BCMI, monitoring which states is active is applied during SSVEP gazing as an extended control option - a switch that can be used to add an extra mapping to an SSVEP choice. For example, when SSVEP is used to select a specific visual pattern for the string instruments to play, a motor imagery extension can allow for the hybrid BCMI to select either the viola or the violin.

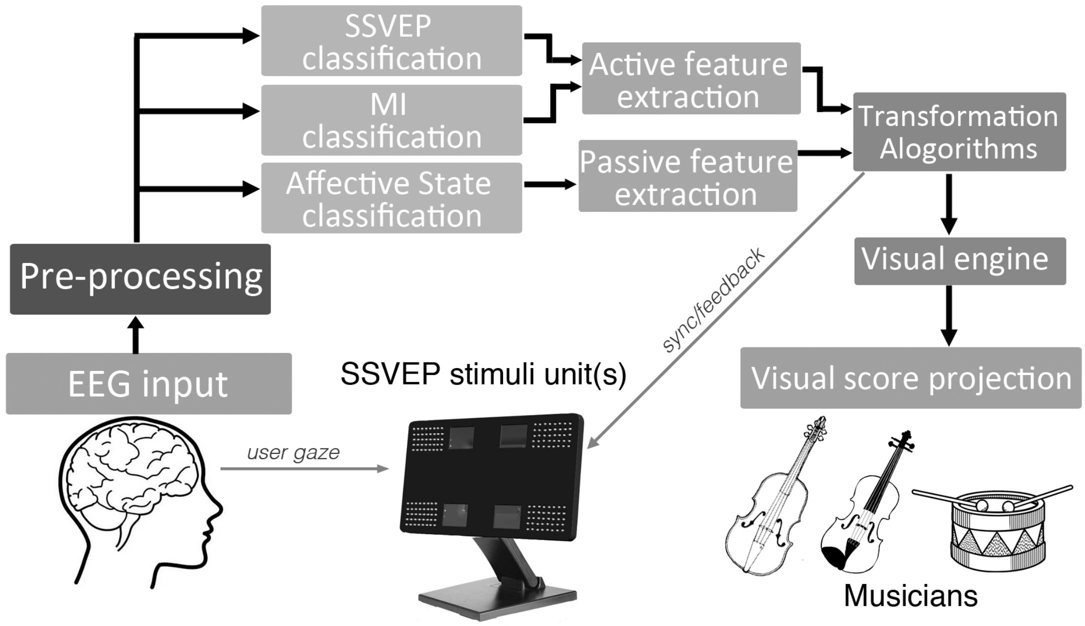

Figure 20: Diagram of the hybrid BCMI system for *A Stark Mind*. Features from the three methods of control are extracted from EEG and mapped to parameters of the visual score through transformation algorithms.

The integration of three control methods in the hybrid BCMI not only increases the amount of options available for a user but it allows for simultaneous musical control across three EEG dimensions (Figure 20). This simultaneous control provides the BCMI equivalent of polyphony, a concept ingrained in many traditional musical interfaces. Combining two methods of *active* control (SSVEP and motor imagery), coupled with the *passive* control method of mapping affective responses to music, demonstrates a unique application of how BCMI systems can push the boundaries of creativity in computer music.

5 CONCLUDING REMARKS

In this chapter we introduced four illustrative projects in the field of Music Neurotechnology, ranging for development of basic research and pragmatic systems targeted to medical applications, to more subjective creative works. We hope to have demonstrated how Biology, more specifically, Neurobiology, can inform and inspire musical research and new developments in music technology.

Practical outcomes from research into developing biochips with *in vitro* neuronal networks are likely to be something for the distant future. We reckon that progress at this front will occur in tandem with progress in the field of Synthetic Biology, which is looking into synthesising neurones artificially. In the meantime, computer models provide a viable way to explore the behaviour of neuronal networks for composition.

As for the BCMI research, currently most EEG-music initiatives do not employ adequate hardware. Unfortunately, there are a number of low cost pieces of EEG equipment in the market that do not perform as well as their manufacturers advertise. Practitioners' general lack of technical knowledge tend to use these due to budgetary constrains, which ends up being a false economy: research progress is hindered due to lack of EEG measure precision. Moreover, EEG-music initiatives are largely based on rather simplistic direct sonification of the EEG signal, which often is contaminated by noise due to low quality of the equipment used. It is hoped that cost-effective equipment of reasonable good quality become more affordable in the near future and artists might soon benefit from more scientifically robust techniques to use EEG to control musical systems. As the kinds of EEG control methods that we tested in the piece *A Stark Mind* evolve in sophistication, we hope that more possibilities will be available for BCMI designers and composers.

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