

# Biologically-driven Musical Instrument

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**Abstract**—This project proposes to use the analysis of physiological signals (electroencephalogram (EEG), electromyogram (EMG), heart beats) to control sound synthesis algorithms in order to build a biologically driven musical instrument. This project took place during the eNTerFACE'05 summer workshop in Mons, Belgium. Over four weeks specialists from the fields of brain computer interfaces and sound synthesis worked together to produce playable biologically controlled musical instruments. Indeed, a "bio-orchestra", with three new digital musical instruments controlled by physiological signals of two bio-musicians on stage, was offered to a live audience.

**Index Terms**—eNTerFACE'05; Electroencephalogram; EEG; Electromyogram; EMG; Biological signal; Brain Computer Interface; BCI; Music; Sound Synthesis; Sound Mapping.

## I. INTRODUCTION

RECENTLY there has been much theoretical discourse about the symbiotic relationship between Art and Science. This is likely due to the fact that, for many years, Art and Science were artificially segregated as two distinct and mutually exclusive activities. Science was seen as a rigorous, methodical practice and Art as an expression of inner states, thoughts and emotions. Much recent work - including this project - attempts to develop a hybrid approach to solving complex scientific and aesthetic problems.

Advances in computer science and specifically in Human-Computer Interaction (HCI) have now enabled musicians to use sensor-based computer instruments to perform music [1]. Musicians can now use positional, cardiac, muscle and other sensor data to control sound [2], [3]. Simultaneously, advances in Brain-Computer Interface (BCI) research have shown that cerebral patterns can be used as a source of control [4]. Indeed, cerebral and conventional sensors can be used together, [5], [6] with the object of producing a 'body-music' controlled according to the musician's imagination and proprioception. Some research has already been done toward integrating BCI and sound synthesis with two very different approaches. The

This report, as well as the source code for the software developed during the project, is available online from the eNTerFACE'05 web site: [www.enterface.net](http://www.enterface.net).

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first approach aims to sonify data issued from physiological analysis by transforming them in sound [7] [8] [9]. This process can be viewed as a translation of physiological signals into sound. The second approach aims to build a musical instrument [6]. In this case, the musician tries to use his physiological signals to control intentionally the sound production. This is easy for EMG or electro-oculogram (EOG) but difficult for heart sound or electroencephalogram (EEG). At the beginning of this workshop, we did not know which approach we would choose and it became the subject of numerous discussions. In the following, we first present a short history of biological instruments and then present the architecture we developed to acquire, process and play music based on biological signals. Next we go into more detail on signal acquisition part followed by an in-depth discussion of appropriate signal processing techniques. Details of the sound synthesis implementation are then discussed along with the instruments we built. Finally, we conclude and present some future directions.

## II. HISTORY

Brainwaves are a form of bioelectricity, or electrical phenomena in animals or plants. Human brainwaves were first measured in 1924 by Hans Berger, at the time an unknown German psychiatrist. He termed these electrical measurements the electroencephalogram (EEG), which literally means brain electricity writing. Berger published his brainwave results in 1929 as "Über das Elektrenkephalogramm des Menschen" ("On the Electroencephalogram of Man") [10]. The English translation did not appear until 1969. His results were verified by Matthews et al in 1934 who also attempted to sonify the measured brainwave signals in order to listen to them as reported in the journal *Brain*. This was the first example of the sonification of human brainwaves for auditory display.

If we accept that the perception of an act as art is what makes it art, then the first instance of the use of brainwaves to generate music did not occur until 1965. Alvin Lucier [11] had begun working with physicist Edmond Dewan in 1964, performing experiments that used brainwaves to create sound. The next year, he was inspired to compose a piece of music using brainwaves as the sole generative source. Music for Solo Performer was presented, with encouragement from John Cage, at the Rose Art Museum of Brandeis University in 1965. Lucier performed this piece several more times over the next few years, but did not continue to use EEG in his own compositions.

In the late 1960s, Richard Teitelbaum was a member of the innovative Rome-based live electronic music group *Musica Elettronica Viva* (MEV). In performances of *Spacecraft*

(1967) he used various biological signals including brain (EEG) and cardiac (ECG) signals as control sources for electronic synthesizers. Over the next few years, Teitelbaum continued to use EEG and other biological signals in his compositions and experiments as triggers for nascent Moog electronic synthesizers.

Then in the late 1960s, another composer, David Rosenboom, began to use EEG signals to generate music. In 1970- 71 Rosenboom composed and performed *Ecology of the Skin*, in which ten live EEG performer-participants interactively generated immersive sonic/visual environments using custom-made electronic circuits. Around the same time, Rosenboom founded the Laboratory of Experimental Aesthetics at York University in Toronto, which encouraged pioneering collaborations between scientists and artists. For the better part of the 1970s, the laboratory undertook experimentation and research into the artistic possibilities of brainwaves and other biological signals in cybernetic biofeedback artistic systems. Many artists and musicians visited and worked at the facility during this time including John Cage, David Behrman, LaMonte Young, and Marian Zazeela. Some of the results of the work at this lab were published in the book “Biofeedback and the Arts” [12]. A more recent 1990 monograph by Rosenboom, “Extended Musical Interface with the Human Nervous System” [13], remains the definitive theoretical document in this area.

Simultaneously, Manfred Eaton was also building electronic circuits to experiment with biological signals at Orcus Research in Kansas City. He initially published an article titled “Biopotentials as Control Data for Spontaneous Music” in 1968. Then, in 1971, Eaton first published his manifesto “Bio-Music: Biological Feedback Experiential Music Systems” [14], arguing for completely new biologically generated forms of music and experience.

In France, scientist Roger Lafosse was doing research into brainwave systems and proposed, along with musique concrète pioneer Pierre Henry, a sophisticated live performance system known as Corticalart (art from the cerebral cortex). In a series of free performances done in 1971, along with generated electronic sounds, one saw a television image of Henry in dark sunglasses with electrodes hanging from his head, projected so that the content of his brainwaves changed the colour of the image according to his brainwave patterns.

In 1990 two scientists, Benjamin Knapp and Hugh Lusted [15], began working on a computer interface called the BioMuse. It permitted a human to control certain computer functions via bioelectric signals primarily via EMG. In 1992, Atsu Tanaka [1] was commissioned by Knapp and Lusted to compose and perform music using the BioMuse as a controller. Tanaka continued to use the BioMuse, primarily as an EMG controller, in live performances throughout the 1990s. In 1996, Knapp and Lusted wrote an article for *Scientific American* about the BioMuse entitled “Controlling Computers with Neural Signals”.

Starting in the early 1970s, Jacques Vidal, a computer science researcher at UCLA, began working to develop the first direct brain-computer interface (BCI) using an IBM mainframe com-

puter and other custom data acquisition equipment. In 1973, he published “Toward Direct Brain-Computer Communication” [16].

In 1990 Jonathan Wolpaw et al [17] at Albany developed a system to allow a user rudimentary control over a computer cursor via the alpha band of their EEG spectrum. Around the same time, Christoph Guger and Gert Pfurtscheller began researching and developing BCI systems along similar lines in Graz, Austria [18].

In 2002, the principal BCI researchers in Albany and Graz published a comprehensive survey of the state of the art in BCI research, Brain-computer interfaces for communication and control [4]. Then in 2004 an issue dedicated to the broad sweep of current BCI research was published in *IEEE Biomedical Transactions* [19].

### III. ARCHITECTURE

We intend to build a robust architectural framework that could be reuse with other biological data, other analysis and other instrument. Therefore the signal acquisition, the signal processing and the sound synthesis are operated on different virtual machines that communicate by the network (Fig. 1). The data from the different modalities are recorded on different machines. Once acquired the data are sent to a Simulink [20] program. Then they are processed before to be sent with Open Sound Control [21] to the musical instruments and the sound spatialization and visualization. The musical instrument are build with Max/MSP [22]. Below is a outline of the main software and data exchange architecture.

#### A. Software

1) *Matlab and Simulink*: Biosignal analysis is achieved with various methods including wavelet analysis and spatial filter. Due to the flexibility of Matlab [20] programming, all the algorithms are written in Matlab code. However since the signal acquisition from the EEG cap is made in C++ we first used a method in C++ that called the Matlab codes. We know that EEG activity varies from a person to another, thus, in order to have a good adaptation to all subjects and change parameters like frequency bands online, we implemented our sources in a Simulink [20] block diagram using Level-2 M file S-functions with tuneable parameters for our methods. This allows us to adapt online to the incoming signals from the subjects scalp. Subsequently, we can proceed with a real-time, manually controlled, adaptive analysis. Simulink offers many possibilities in terms of visualisation. For example, we used the virtual reality toolbox in order to have some feedback and help the user control his/her EEG. The graphical interface used here is quite simple and consist of a ball moving to the right or to the left whether the user is moving is right or left hand.

2) *Max/MSP*: Max/MSP [22] is a software programming environment optimised for flexible real-time control of music systems. It was first developed at IRCAM by Miller Puckette as a simplified front end controller for the 4X series of mainframe music synthesis systems. It was further developed as a commercial product by David Zicarelli [23] and others at Opcode Systems and Cycling 74 [24]. It is

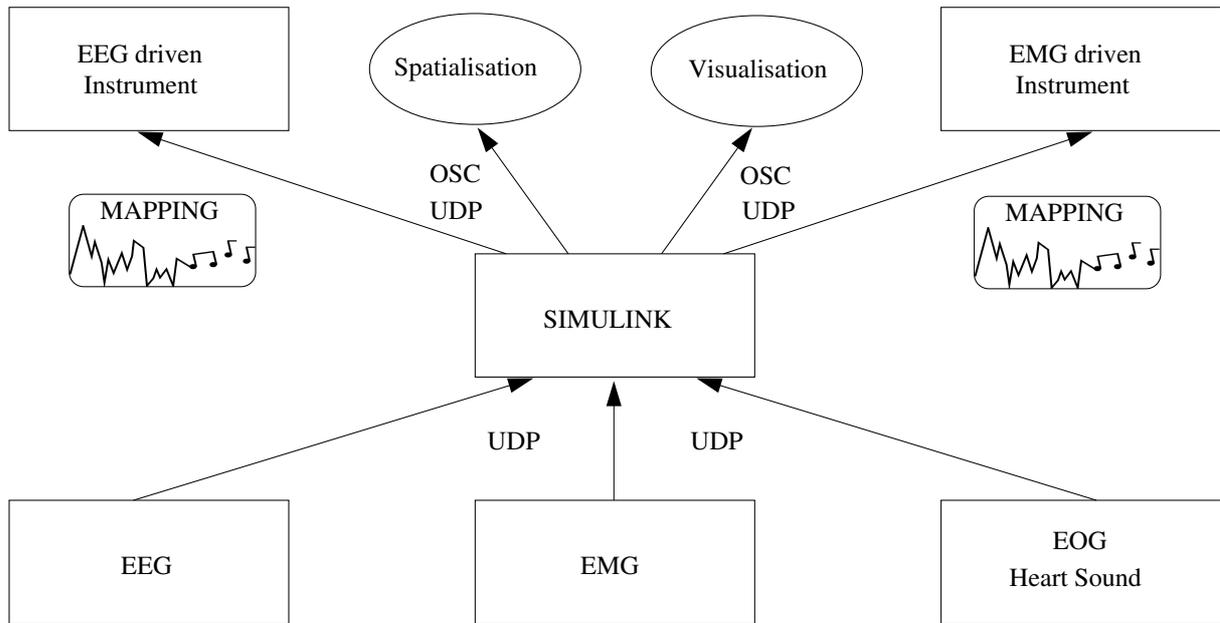


Fig. 1. System architecture

currently the most popular environment for programming of real-time interactive music performance systems. Max/MSP is interesting to use in that is a very mature, widely accepted and supported environment. The result of this is that few problems are encountered which cannot be resolved simply with recourse to the many available support resources. There are, however, some concerns about its continued use in an academic environment where open-source software systems are increasingly preferred or even required. There are other open-source environments which could be more interesting in the long-term especially in an academic context: Pure Data and jMax are both open-source work-alike software implementations which although not as mature as Max/MSP are nonetheless very usable. SuperCollider is another, text-based, programming environment which is also very powerful but is somewhat more arcane and difficult to program.

**B. Data Exchange**

Data are transferred from one machine to another with the UDP protocol. We chose it mainly for its better real-time capability. To communicate with the musical instrument we use a specific protocol one level higher than UDP: open sound control (OSC) [21].

1) *Open Sound Control*: OSC [21] was conceived as a protocol for the real-time control of computer music synthesizers over modern heterogeneous networks. Its development was informed by shortcomings experienced with the established MIDI standard and the difficulties in developing a more flexible protocol for effective real-time control of expressive music synthesis. Various attempts had been made to produce a replacement for the MIDI protocol such as ZIPI which was proposed and then abandoned. OSC was first proposed by Matthew Wright and Adrian Freed in 1997. Since that time its use and development have grown such that it is becoming very widely implemented in software and hardware

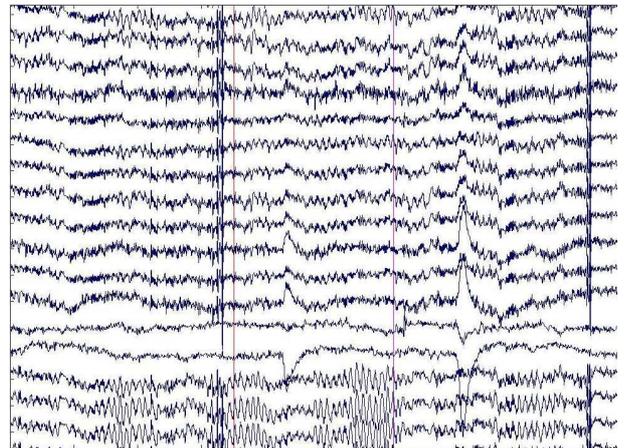


Fig. 2. EEG signals

designs (although, still not as widespread as MIDI). Although it can function in principle over any appropriate transport layer such as WiFi, serial, USB or other data network, current implementations of OSC are optimised for UDP/IP transport over Fast Ethernet in a Local Area Network. For our project, we used OSC to transfer data from Matlab (running on a PC with either Linux or Windows OS) towards Max/MSP (running on a Macintosh OSX).

**IV. DATA ACQUISITION**

Four types of data are considered with associated captors: ECG, EMG, EEG and EOG data. ECG, EMG and EOG are acquired on one machine and EEG on another.

**A. EEG**

EEG data (Fig. 2) are recorded at 64 Hz on 19 channels with a DTI cap. Data are filtered between 0.5 and 30 Hz. Channels

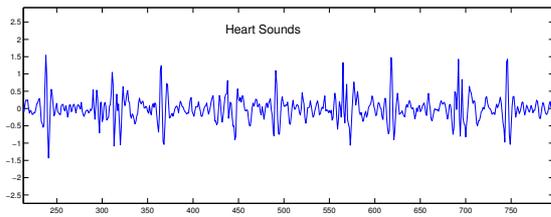


Fig. 4. heart signal

are positioned following the 10-20 international system and Cz is used as reference. The subject sit in a comfortable chair and is asked to concentrate on the different tasks. The recording is done in normal working place, e.g. a noisy room with people working, speaking and with music. The environment is not electrical noise free as there are many computers, speakers, screen, microphones and lights around.

*B. Electromyogram (EMG), heart sound and Electrooculogram (EOG)*

To record the EMG (Fig. 3) and heart sounds (Fig. 4), three amplifiers of Biopac MP100 system were used. The amplification factor for the EMG was 5000 and the signals were filtered between 0.05-35 Hz. The microphone channel has 200 gain and DC-300Hz bandwidth. Another 2 channel amplifier, ModularEEG is used to collect the EOG signals (Fig. 5).

This amplifier has 4000 gain and 0.4-60Hz passband. For real time capabilities, these amplified signals are fed to the National Instruments DAQPad 6052e analog-digital converter card that uses the IEEE 1394 port. Thus, the data can be acquired, processed and transferred to the musical instruments using Matlab environment and the Data Acquisition toolbox.

Disposable ECG electrodes were used for both EOG and EMG recordings. The sounds were captured using the Biopac BSL contact microphone. The locations of electrodes are shown in Fig. 6.

**V. BIOSIGNAL PROCESSING**

The aim of this work is to control sound and synthesise music using parameters derived from measured biological signals such as: EEG, EOG, EMG and heart sounds. We therefore have tested different techniques to extract parameters giving meaningful control data to drive musical instruments. We mainly concentrated on EEG signal processing as it is the richest and most complex bio-signal. The musician normally has better conscious control over bio-signals other than EEG and therefore only basic signal processing is done in these cases. The data acquisition program samples blocks of EMG or EOG data of 100 ms duration, and then analyses this data. It calculates the energy for the EOG and EMG channels, and sends this information to the related instruments. The heart sound itself is directly sent to the instruments to provide a background motif, which can be also used to control the rhythmic structure. The waveform can also be monitored on the screen in real-time.

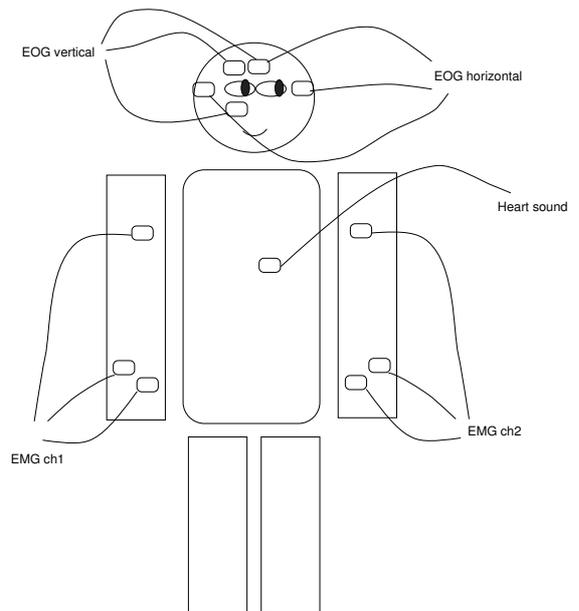


Fig. 6. Application of multiple electrodes and transducers

Two kinds of EEG analysis are done. The first one focuses on the detection of a users intent. It is based on the work being done in the BCI community [4]. A second approach looks at the origin of the signal and at the activation of different brain areas. The musician has less control over results in this case. At the end of this section there are more details on both of these EEG analysis approaches (Fig. 7).

*A. Detection of Musical Intent*

To detect different brain states we used the spatialisation of the activity and the different rhythms present in this activity. Indeed, each part of the brain has a different function and each human being presents specific rhythms at different frequencies.

For example, three main rhythms are of great interest:

- 1) Alpha rhythm: usually between 8-12 Hz, this rhythm describes the state of awareness. If we calculate the energy of the signal using the occipital electrodes, we can evaluate the awarness state of the musician. When he closes his eyes and relaxes the signal increases. When the eyes are open the signal is low.
- 2) Mu rhythm: This rhythm is also reported to range from 8 to 12 Hz but this band can vary from one person to another, sometimes between 12-16 Hz. The mu rhythm corresponds to motor tasks like moving the hands or legs, arms, etc. We use this rhythm to distinguish left hand movements from right hand movements.
- 3) Beta rhythm: Comprised of energy between 18-26 Hz, the characteristics of this rhythm are yet to be fully understood but it is believed that it is also linked to motor tasks and higher cognitive function.

Therefore the well-known wavelet transform [25] is a technique of time-frequency analysis perfectly suited for the task detection. Each task can be detected by looking at specific bandwidth on specific electrodes.

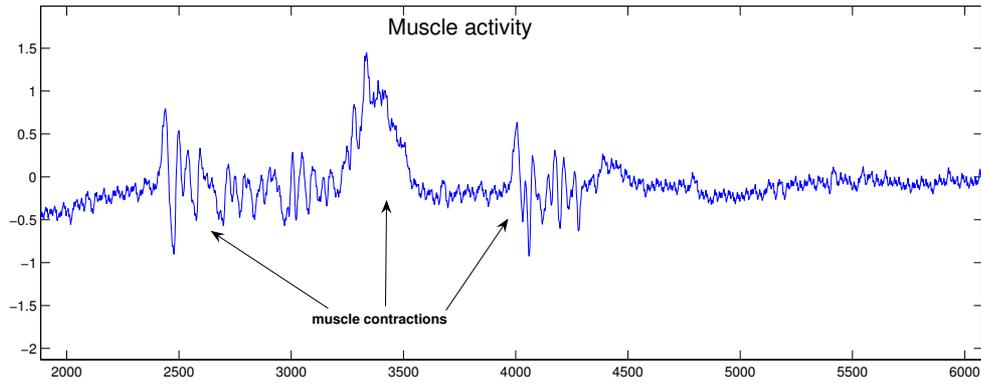


Fig. 3. EMG signal

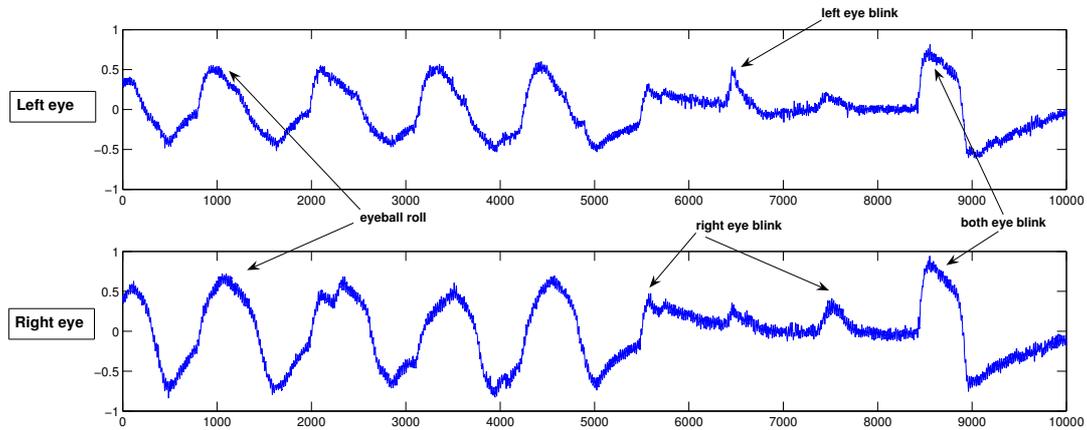


Fig. 5. EOG signal

This operation, implemented with sub-band filters, provides us with a filter bank tuned to the frequency ranges of interest. We tested our algorithm on two subjects with different kinds of wavelets: Meyer wavelet, 9-7 filters, bi-orthogonal spline wavelet, Symlet 8 and Daubechey 6 wavelets. We finally chose the symlet 8 which gave better overall results. Once the desired rhythms are obtained, different forms of analysis are possible.

At the beginning we focused on eye blink detection and  $\alpha$  band power detection because both are easily controllable by the musician. We then wanted to try more complex tasks such as those used in the BCI community. These are movements and imaginations of movements, such as hand, foot or tongue movements, 3D spatial imagination or mathematical calculation. The main problem is that each BCI user needs a lot of training to improve his control of the task signal. Therefore we decided to use only right and left hand movements first and not the more complex tasks which would have been harder to detect. Since more tasks also means more difficult detection, there are the only tasks used in this project. Two different techniques were used: Asymmetry ratio and spatial decomposition.

1) *Eye blinking and  $\alpha$  band*: Eye blinking is detected on Fp1 and Fp2 electrodes in the 1-8Hz frequency range by

looking at increase of the band power. We process the signals from electrodes O1 and O2 -occipital electrodes- to extract the power of the alpha band.

2) *Asymmetry ratio*: Consider we want to distinguish left from right hand movements. It is known that motor tasks activate the cortex area. Since the brain is divided in two hemispheres that control the two sides of the body it is possible to recognise when a person moves on the left or right side. Let C3 and C4 be the two electrodes positioned on the cortex, the asymmetry ratio can be written as:

$$\Gamma_{FB} = \frac{P_{C3,FB} - P_{C4,FB}}{P_{C3,FB} + P_{C4,FB}} \quad (1)$$

where  $P_{C_{x,FB}}$  is the power in a specified frequency band (FB), i.e. the mu frequency band. This ratio has values between 1 and -1. Thus it is positive when the power in the left hemisphere (right hand movements) is higher than the one in the right hemisphere (left hand movements) and vice-versa.

The asymmetry ratio gives good results but is not very flexible and cannot be used to distinguish more than two tasks. This is why it is necessary to search for more sophisticated methods which can process more than just two electrodes as the asymmetry ratio does.

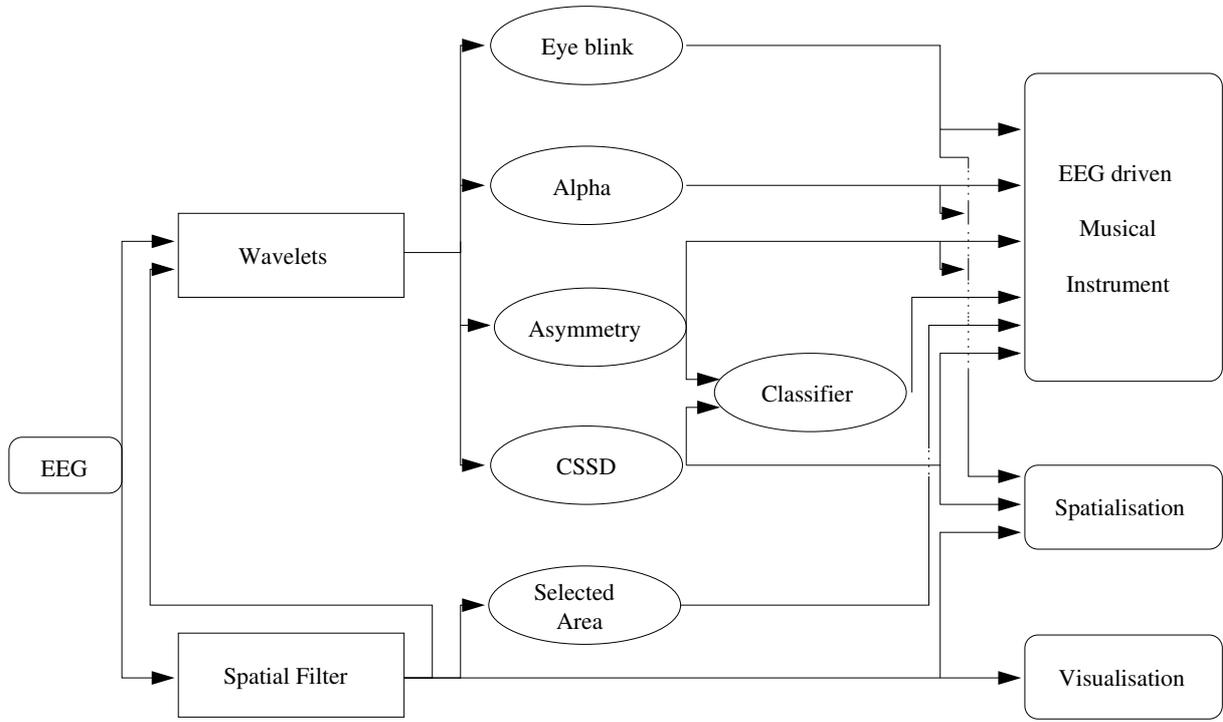


Fig. 7. EEG processing, from recording (left) to play (right).

3) *Spatial decomposition*: Two spatial methods have proven to be accurate: The Common Spatial Patterns (CSP) and the Common Spatial Subspace Decomposition (CSSD) [26], [27]. We will shortly describe here the second one (CSSD): This method is based on the decomposition of the covariance matrix grouping two or more different tasks. Only the simple case of two tasks will be discussed here. It is important to highlight the fact that this method needs a learning phase where the user executes the two tasks.

The first step is to compute the autocovariance matrix for each task. Lets take one signal  $X$  of dimension  $N \times T$  for  $N$  electrodes and  $T$  samples. Decomposing  $X$  in  $X_A$  et  $X_B$ ,  $A$  and  $B$  being two different tasks, we can obtain the autocovariance matrix for each task:

$$R_A = X_A X_B^T \quad \text{and} \quad R_B = X_B X_B^T \quad (2)$$

We now extract the eigenvectors and eigenvalues from the  $R$  matrix that is the sum of  $R_A$  and  $R_B$ :

$$R = R_A + R_B = U_0 \lambda U_0^T \quad (3)$$

We can now calculate the spatial factors matrix  $W$  and the whitening matrix  $P$ :

$$P = \lambda^{-1/2} U_0^T \quad \text{and} \quad W = U_0 \lambda^{1/2} \quad (4)$$

If  $S_A = P R_A P^T$  and  $S_B = P R_B P^T$ , these matrices can be factorised:

$$S_A = U_A \Sigma_A U_A^T \quad S_B = U_B \Sigma_B U_B^T \quad (5)$$

Matrix  $U_A$  et  $U_B$  are equals and the sum of their eigenvalue is equal to 1,  $\Sigma_A + \Sigma_B = I$ .  $\Sigma_A$  et  $\Sigma_B$  can be written thus:

$$\Sigma_A = \text{diag} \left[ \underbrace{1 \dots 1}_{m_a} \quad \underbrace{\sigma_1 \dots \sigma_{m_c}}_{m_c} \quad \underbrace{0 \dots 0}_{m_b} \right] \quad (6)$$

$$\Sigma_B = \text{diag} \left[ \underbrace{0 \dots 0}_{m_a} \quad \underbrace{\delta_1 \dots \delta_{m_c}}_{m_c} \quad \underbrace{1 \dots 1}_{m_b} \right] \quad (7)$$

Taking the first  $m_a$  eigenvector from  $U$ , we obtain  $U_a$  and we can now compute the spatial filters and the spatial factors:

$$S P_a = W U_a \quad (8)$$

$$S F_a = U_a^T P \quad (9)$$

We proceed identically for the second task, but taking this time the last  $m_b$  eigenvectors. Specific signal components of each task can then be extracted easily by multiplying the signal with the corresponding spatial filters and factors. For the task A it gives:

$$\hat{X}_a = S P_a S F_a X \quad (10)$$

A support vector machine (SVM) with a radial basis function was used as a classifier.

4) *Results*: The detection of eye blinking during off-line and realtime analysis was higher than 95%, with a 0.5s time window. For hand movement classification with spatial decomposition, we chose to use a 2s time window. A smaller window significantly decreases the classification accuracy. The algorithm CSSD needs more training data to achieve a good classification rate so we decided to use 200 samples of both right hand and left hand movements, each sample being a 2s time window. Thus, we used an off-line session to train the algorithm. However each time we used the EEG cap for a new

session, the electrode locations on the subject's head changed. Performing a training session one time and a test session another time gave poor results so we decided to develop new code in order to do both training and testing in one session. This had to be done quite quickly to ensure the user's comfort.

We achieved an average of 90% good classifications during off-line analysis, and 75% good classifications during real-time recording. Real-time recording accuracy was a bit less than expected. (This was probably due to a less-than-ideal environment - with electrical and other noise - which is not conducive to accurate EEG signal capture and analysis.) The asymmetry ratio gave somewhat poorer results.

## B. Spatial Filters

EEG is a measure of electrical activities of the brain as measured on the external skull area. Different brain processes can activate different areas. Thus, knowing which areas are active can inform us as to active cerebral processes. Discovering which areas are active is difficult as many source configurations can lead to the same EEG recording. Noise in the data further complicates the problem. The ill-posedness of the problem leads to many different methods based on different hypotheses to get a unique solution. In the following, we present the methods - based on forward and inverse problems - and the hypothesis we propose to solve the problem in real time.

1) *Forward Problem, head model and solution space:* If  $X$  is a  $N \times 1$  vector containing the recorded potential with  $N$  representing the number of electrodes.  $S$  is an  $M \times 1$  vector of the true source current with  $M$  the unknown number of sources.  $G$  is the leadfield matrix which links the source location and orientation to the electrodes location.  $G$  depends of the head model.  $n$  is the noise. We can write

$$X = G S + n \quad (11)$$

$X$  and  $S$  can be extended to more than one dimension to take time into account.  $S$  can either represent few dipoles (dipole model) with  $M \leq N$  or represent the full head (image model - one dipole per voxel) with  $M \gg N$ . In the following we will use the latter model.

The forward problem is to try and find the potentials  $X$  on the scalp surface knowing the active brain sources  $S$ . This approach is far simpler than the inverse approach and its solution is the basis of all Inverse problem solutions.

The leadfield  $G$  is based on the Maxwell equations. A finite element model based on the true subject head can be used as lead field but we prefer to use a 4-spheres approximation of the head. It is not subject dependent and less computationally expensive. A simple method consists of seeing the multi-shell model as a composition of single-shells -much as Fourier uses functions as sums of sinusoid [28]. The potential  $v$  measured at electrode position  $r$  from a dipole  $q$  in position  $r_q$  is

$$v(r, r_q, q) \approx v^1(r, \mu_1 r_q, \lambda_1 q) + v^1(r, \mu_2 r_q, \lambda_2 q) + v^1(r, \mu_3 r_q, \lambda_3 q) \quad (12)$$

$\lambda_i$  and  $\mu_i$  are called Berg's parameters [28]. They have been empirically computed to approximate three and four-shell head model solution.

When we are looking for the location and orientation of the source, a better approach consists of separating the non-linear search for the location and the linear one for the orientation. The EEG scalar potential can then be seen as a product  $v(r) = k^t(r, r_q)q$  with  $k(r, r_q)$  a  $3 \times 1$  vector. Therefore each single shell potential can be computed as [29]

$$v^1(r) = ((c_1 - c_2(r, r_q))r_q + c_2 \|r_q\|^2 r) \cdot q$$

with

$$c_1 \equiv \frac{1}{4\pi\sigma \|r_q\|^2} \left( 2 \frac{d \cdot r_q}{\|d\|^3} + \frac{1}{\|d\|} - \frac{1}{\|r\|} \right) \quad (13)$$

$$c_2 \equiv \frac{1}{4\pi\sigma \|r_q\|^2} \left( \frac{2}{\|d\|^3} + \frac{\|d\| + \|r\|}{\|r\| \|F(r, r_q)\|} \right) \quad (14)$$

$$F(r, r_q) = \|d\|(\|r\| \|d\| + \|r\|^2 - (r_q \cdot r)) \quad (15)$$

The brain source space is limited to 361 dipoles located on an half-sphere just below the cortex in a perpendicular orientation to the cortex. This is done because the activity we are looking at is concentrated on the cortex, the activity recorded by the EEG is mainly cortical activity and the limitation of the source space considerably reduces the computation time.

2) *Inverse Problem:* The inverse problem can be formulated as a Bayesian inference problem [30]

$$p(S|X) = \frac{p(X|S)p(S)}{p(X)} \quad (16)$$

where  $p(x)$  stands for probability distribution of  $x$ . We thus look for the sources with the maximum probability. Since  $p(X)$  is independent of  $S$  it can be considered as an normalizing constant and can be omitted.  $p(S)$  is the prior probability distribution of  $S$  and represents the prior knowledge we have about the data. This is modified by the data through the posterior probability distribution  $p(X|S)$ . This probability is linked to the noise. If the noise is gaussian - as everybody assumed - with zero mean and covariance matrix  $C_n$

$$\ln p(X|S) = (X - GS)^t C_n^{-1} (X - GS) \quad (17)$$

where  $^t$  stands for transpose. If the noise is white, we can rewrite equation (17) as

$$\ln p(X|S) = \|X - GS\|^2 \quad (18)$$

In case of zero mean gaussian prior  $p(S)$  with variance  $C_S$ , the problem becomes

$$\begin{aligned} & \operatorname{argmax}(\ln p(S|X)) \\ &= \operatorname{argmax}(\ln p(X|S) + \ln p(S)) \\ &= \operatorname{argmax}((X - GS)^t C_n^{-1} (X - GS) + \lambda S^t C_S S) \end{aligned}$$

where the parameter  $\lambda$  gives the influence of the prior information. And the solution is

$$\hat{S} = G^t C_n^{-1} (G^t C_n^{-1} G + \lambda C_S^{-1})^{-1} X \quad (19)$$

For a full review of method to solve the Inverse Problem see [30]–[32].

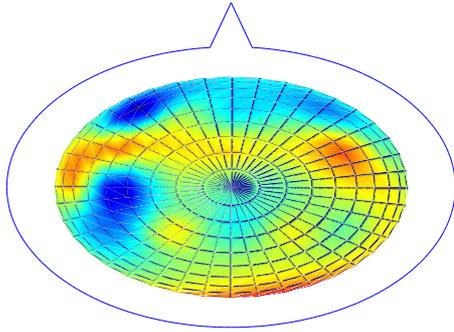


Fig. 8. Derived current at the surface of the brain. The scale is going from blue the more negative potential to red the more positive potential

Methods based on different priors were tested. Priors ranged from the simplest -no prior information- to classical prior such as the laplacian and to a specific covariance matrix. The well-know LORETA approach [32] showed the best results on our test set. The LORETA [32] looks for a maximally smooth solution. Therefore a laplacian is used as a prior. In (19)  $C_s$  is a laplacian on the solution space and  $C_n$  is the identity matrix.

To enable real time computation, leadfield and prior matrices in (19) are pre-computed. Then we only multiply the pre-computed matrix with the acquired signal. Computation time is less than 0.01s on a typical personal computer.

3) *Results and Application:* In the present case of a BCMI, the result can be use for three potential applications: the visualisation process, a pre-filtering step and a processing step.

The current of the 361 dipoles derived using the inverse method is directly used in the visualisation process. The current on every point of the half-sphere is interpolated from the dipole currents. The result is projected on a screen (see Fig. 8). The result of the inverse solution could be use as a pre-filtering step in the classification process. Instead of using the 18 electrode signals, the 361 dipole signals can be used. We did not have enough time to test this approach.

The results of the inverse solution reflect the brain activity. Therefore it could be used as direct control data for our musical instrument. Four brain areas were selected. They were the frontal area, the occipital area and both left and right sensori-motor and motor areas. The frontal area is generally linked to cognition and memory processes. Left and right sensori-motor and motor cortex areas are linked to movement and imagination of movement in the right and left parts of the body respectively. The occipital area is inferred in visualisation processes. For every area, we compute the mean of the source signal in the area. The mean of each area is then scaled and sent as control data for the musical instruments. The dipoles inside each area were selected on a visual basis in order to adequately cover the relevant areas (Fig. 9).

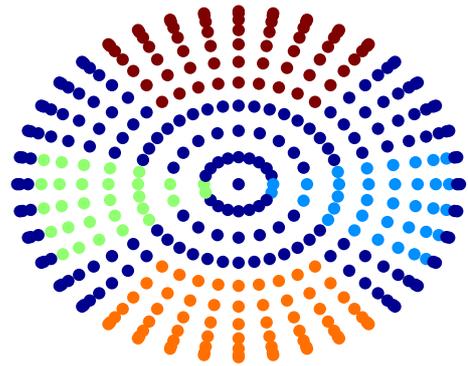


Fig. 9. Dipoles are set in 4 areas. Dark blue dipoles are outside all the area. Light blue dipoles are in right sensorimotor and motor cortex area. Green dipoles aare in left sensorimotor and motor cortex area. Orange dipoles are in occipital area. Brown dipoles are in frontal area

## VI. SOUND SYNTHESIS

### A. Introduction

1) *Sound Synthesis:* Artificial synthesis of sound is the creation, using electronic and/ or computational means, of complex waveforms, which, when passed through a sound reproduction system can either mimic a real musical instrument or represent the virtual projection of an imagined musical instrument. This technique was first developed using digital computers in the late 1950s and early 1960s by Max Matthews at Bell Labs. It does have antecedents, however, in the musique concrte experiments of Pierre Schaeffer and Pierre Henry and in the TelHarmonium of Thaddeus Cahill amongst others. The theory and techniques of sound synthesis are now widely developed and are treated in depth in many well-known sources.

The chosen software environment, Max/MSP, makes available a wide palette of sound synthesis techniques including: additive, subtractive, frequency modulation, granular etc. With the addition of 3rd party code libraries (externals) Max/MSP can also be used for more sophisticated techniques such as physical modelling synthesis.

2) *Mapping:* The very commonly used term mapping refers, in the instance of virtual musical instruments, to mathematical transformations which are applied to real-time data received from controllers or sensors so that they may be used as effective control for sound synthesis parameters. This mapping can consist of a number of different mathematical and statistical techniques. To effectively implement a mapping strategy one must understand well both the ranges and behaviour of the controller or sensor data and the synthesis parameters which are to be controlled. For our purposes, it is most important to be mindful of the appropriate technique to be used in order to achieve the desired results.

A useful way of thinking about mapping is to consider its origin in the art of making cartographic maps of the natural world. Mapping thus is forming a flat, virtual representation of a curved, spherical real world which enables that real world

to be effectively navigated. Implicit in this is the process of transformation or projection which is necessary to form the virtual representation. This projection is not a transparent process but can involve decisions and value judgements. The commonly-used Mercator projection of the world, for example, gives greater apparent land mass and thus import to the western and northern parts of the world where that projection was initially developed and used. Buckminster Fuller attempted to redress this issue with his Geodesic projection of the world which was felt to be a more accurate representation of the earth's surface.

Thus, to effectively perform a musically satisfying mapping, we must understand well the nature of our data sources (sensors and controllers), the nature of the sounds and music we want to produce (including intrinsic properties and techniques of sound synthesis, sampling, filtering and DSP)

This poses significant problems in the case of biologically controlled instruments in that it is not possible to have an unambiguous interpretation of the meanings of biological signals whether direct or derived. There is some current research in cognitive neuroscience which may indicate directions for understanding and interpreting the musical significance of encephalographic signals at least.

A simple example is the alpha rhythm or more correctly alpha spectrum of the EEG. It is well known that strong energy in the frequency band (8-13 Hz) indicates a state of unfocused relaxation without visual attention in the subject. This has commonly been used as a primary controller in EEG-based musical instruments such as Alvin Luciers "Music for Solo Performer", where strong EEG will directly translate to increased sound intensity and temporal density. If this is not the desired effect then consideration has to be given to how to transform the given data into the desired sound or music.

At the end of the workshop, a musical bio-orchestra, composed by two new digital musical instruments controlled by two bio-musicians on stage (Fig. 10), offered a live performance to a large audience. The first instrument was a midi instrument based on additive synthesis and controlled by musician's electroencephalograms plus an infrared sensor. The second one, driven by electromyograms of a second bio-musician, processed accordion samples recorded in live situation by granulation and filtering effects. Furthermore biological signals managed the spatialized diffusion over eight loudspeakers of sound produced by both previous instruments and the visual feedback. This was controlled by EEGs of the first bio-musician. We here present details of each of these instruments.

*B. Instrument 1 : a new interface between brain and sound*

EEG analysis can detect many things about eyes and movements, but it needs training to give good results. For this interface, we used the following controls (Fig. 11):

- right or left body part movement (Mu bandwidth)
- eyes are open or closed (Alpha bandwidth)
- the average activity of brain (Alpha bandwidth)

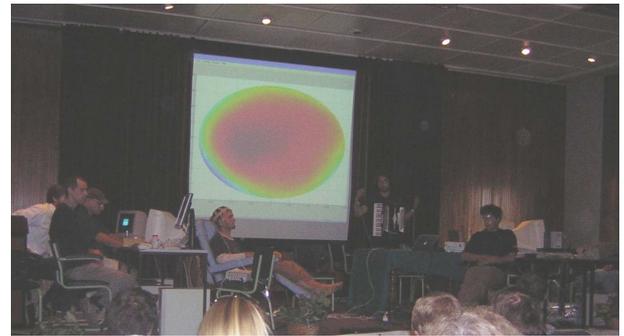


Fig. 10. Concert during eINTERFACE 2005 Workshop

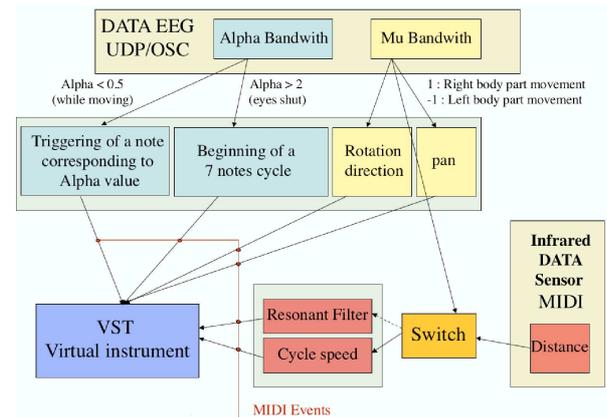


Fig. 11. the fonctionnal instrument diagram

This MAX/MSP patch is based upon these parameters. The sound synthesis is done with a plug-in from Absynth which is software controlled via the MIDI protocol. This patch creates MIDI events which control this synthesis. This synthesis is in particular composed of three oscillators, three Low Frequency Oscillators, and three notch filters. There are two kinds of note trigger:

- a cycle of seven notes
- a trigger of single note

This work needed high-level treatment, so pitch is not controlled continuously. I will try to explain the mapping between sound parameters and control parameters.

Regarding the first kind of note trigger, the cycle of notes begin when the artist opens his eyes for the first time. Then, there is another type of control using EEG analysis, when the artist thinks about right or left body movements, he controls the direction of cycle rotation and the panning of the result. The succession of notes is subjected of two randomised variations, the note durations and the delta time between each note. Regarding the second note trigger, alpha bandwidth is converted to a number between 0 and 3, and is divided into three parts:

- 0 to 1 : this part is divided into five sections, one note is attributed to each section and the time proprieties are given by the dynamics of the alpha variations

- 1 to 2 : represents the variation of the Low Frequency Oscillator (LFO) frequency
- over 2 : the sound is stopped

The EEG analysis for these controls happens over time, and to have an instantaneous control, an infrared sensor controller was added. According to the distance between his hand and the sensor, the artist can control:

- the rotation speed of the cycle, using the right hand
- the frequency of the two other LFO, using the left hand

EEG analysis can detect if the artist moves his right or his left hand, so this one sensor is the source of two kinds of control.

As you can see in the elaboration of this patch, it is already an aesthetic choice in that the performer decides the harmony before playing. This is not the only solution, but in the performance which was done, it has proved to be a good solution (Fig. 10).

Another advantage of this patch is its modularity. An artist can depend on it to create a lots of different sounds results. The patch is a real interface between a synthesis software using MIDI protocol and an EEG analysis with Matlab.

1) *Results:* The aim of this work was to create an instrument commanded by electroencephalogram signals, but can we actually talk about a musical instrument? Instrumental relationships are always linked with gestures. Here no physical interaction is present. Further, the complexity of the interaction with a traditional musical instrument, like a guitar, assigns an important power of manipulation to the artist. To be interesting from an artistic point of view, a musical instrument must give a large expressive space to the artist; this was a big challenge in our case, and it is seems to have been partially effective. In this instrument, the relation between the artist and his production is really peculiar because it acts on two levels: the musician interacts with sound production by means of his EEGs but the produced sound also has a feedback influence on the mental state of the musician. Future work could turn towards the biofeedback influence of sound. When the musician tries to control his brain activities, the sound perturbs him. What kind of influence could there be?

*C. Instrument 2 : Real-time granulation and filtering on accordion samples*

In our second instrument, sound synthesis is based on the real-time granulation and filtering of accordion samples recorded in live situation by the bio-digital musician. During the demonstration, the musician started his performance by playing and recording few seconds of accordion he will then be processed in real-time. Sound processing was implemented thanks to several Max-MSP objects and controlled by means of data extracted from electromyograms (EMGs) measuring both arms muscles contraction of the musician (Fig. 12). An additional MIDI surface control was also used to extend the possibilities of mapping.

1) *Granulation:* Granulation techniques [33] split an original sound into very small acoustic events called grains of 50 ms duration or less, and reproduces them in high densities ranging from several hundred to several thousand



Fig. 12. Bio-musician controlling his musical instrument by means of his muscles contraction

grains per second. A lot of transformations (time stretching, pitch shifting, backward reading) on the original sound are made possible with this technique and a large range of very strange timbres, far from the original, can be obtained in this way. In our instrument, the granulation was achieved by MSP object `munger~`, released as part of the free Max/MSP toolkit `PerColate` developed by Trueman and DuBois [34]. `Munger~` takes an incoming audio signal input and granulates it, breaks it up into small grains which are layered, mixed and transposed as requested, creating cloud-like textures of varying densities. Furthermore, the `munger~` object has several arguments that enable to modify the resulting granulated sound. In order to give the musician the ability, we choose to control three of them:

- the grains size (in ms)
- the pitch shifting : this parameter control the playback speed and allows to transpose all outgoing grains by a multiplier factor.
- the pitch shifting variation (factor between 0 and 1) : `munger~` enables to vary randomly the pitch shifting factor : more precisely, the "grain pitch variation" parameter will control how far into a predefined scale the `munger~` will look for the pitch shifting factor. Increasing this parameter has a strong effect on the resulting sound by making it very turbulent. To enhance this turbulence sensation, we coupled this parameter with swirling spatialization effect. This was the only spatialization effect controlled by the EMG musician, the rest of the spatialization being driven by EEG analysis.

In term of mapping, the performer selected the synthesis parameter he wanted to vary thanks to the midi foot controller and this parameter was then modulated according to the contraction of his arm muscles, measured by electromyograms. The contraction of left arm muscles allowed choosing either to increase or decrease the selected parameter, whereas the variation of the parameter, between predefined range, was directly linked to right arm muscle tension.

2) *Flanging*: We tried some of the most widely used filtering effects in audio processing (chorus, delay, phase shifting etc) and finally we chose to integrate flange effect as filter processing in this first version of our instrument. Flanging is created by mixing a signal with a slightly delayed copy of itself, where the length of the delay, less than 10 ms, is constantly changing (Fig. 13). Instead of creating an echo, the delay has a filtering effect on the signal, and this effect creates a series of notches in the frequency response. This varying delay in the flanger creates some pitch modulation (warbling pitch).

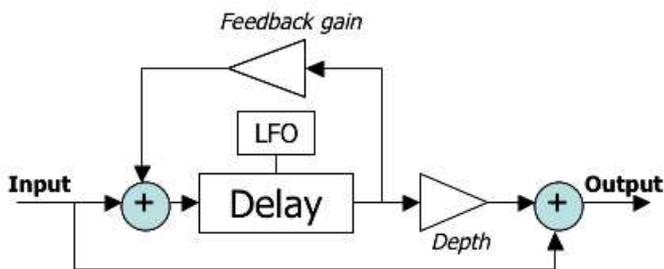


Fig. 13. Diagram of flanger effect. The delay is varying with time thanks to a low frequency oscillator (LFO) whose frequency is user-controllable. The depth parameter allows to control how much of the delayed signal is added to the original one. Feedback gain specifies the amount of feedback signal to be added to the input signal ; a large amount of feedback will create a very 'metallic' and 'intense' sound.

In order to process accordion samples by flange effect, we used in our instrument the example of flange effect provided in the MSP tutorial. The musician chose among different predefined parameters configurations. He had also the ability to modulate each parameter (depth, feedback gain, LFO frequency) separately via his arm muscles contraction, by the same way than for the granulation parameters.

3) *Balance dry/wet sounds*: During the performance, the musician chose to vary whether or not the sound processing parameters (granulation or flange parameters). When the musician does not act on these parameters, he had the possibility to control the intensities of dry and wet sounds with the contraction of his left and right arm respectively. This control gave the musician the ability to cross-fade original sound with the processed one by means of very expressive gestures.

4) *Results*: Very interesting sonic textures, nearer or farther from original accordion sound, have been created by this instrument. Granulation gave the sensation of clouds of sound, whereas very strange sounds, reinforced by spatialisation effects on eight loudspeakers, were obtained using certain parameter configurations of the flange effect. A pleasant way to use this instrument was to superimpose live accordion notes on these synthesised sonic soundscapes such as to create a hyper-accordion. Using arm muscle contractions, measured as EMGs, to control synthesis parameters gave worthwhile results because sound production was controlled via expressive gestures.

5) *Future*: At the end of the workshop, the design of this bio-instrument was just finished. Thus, as with a traditional musical instrument, the first thing to do will be to practice the instrument in order to properly learn it. These training

sessions will especially aim to improve the mapping between sound parameters and gestures, by making it simpler and more intuitive.

Regarding the sound processing/ synthesis itself, trying other kinds of sound processing could give interesting results. Among the difficulties we encountered in designing this instrument controlled by EMG, was the lack of available control parameters extracted from EMGs analysis, hence the need of an additional midi controller to build an entire instrument. Furthermore, this type of mapping relied on arm muscle contractions, which could also be achieved by means of data gloves [35] ; which is why it would be very interesting to add EMGs measuring muscles contraction in other body areas (legs, shoulders, neck) in order to give a real added richness to this bio-instrument.

#### D. Spatialization and Localization

The human perception of the physical location of sound sources within a given physical sound environment are due to a complex series of cues which have evolved according to the physical behaviour of sound in real spaces. These cues can include: intensity, including right- left balance, relative phase, early reflections and reverberation, Doppler shift, timbral shift and many other factors which are actively studied by researchers in auditory perception.

The terms 'spatialisation' and 'localisation' are germane to the study and understanding of this domain. The term 'spatialisation' refers to the creation of a virtual sound space using electronic techniques (analogue or digital) and sound reproduction equipment (amplifiers and speakers) to either mimic the sound-spatial characteristics of some real space or present a virtual representation of an imaginary space reproduced via electronic means. The term 'localisation' refers to the placement of a given sound source within a given spatialised virtual sound environment using the techniques of spatialisation. Given the greatly increased real-time computational power available in today's personal computers, it is now possible to perform complex and subtle spatialisation and localisation of sounds using multiple simultaneous channels of sound reproduction (four or more).

Thus spatialisation is the creation of virtual sound environments and localisation is the placement of given sounds within that virtual environment.

The implementation of a system for the the localisation of individual sound sources and overall spatialisation in this project was based around an 8 channel sound reproduction system. Identical loudspeakers were placed equidistant in a circular pattern around a listening space all at the same elevation - approximately at ear level.

Sounds were virtually placed within the azimuth of this 360 degree circular sound space by the use of mixing software which approximates an equal-power panning algorithm. The amplitude of each virtual sound source can be individually controlled. Artificial reverb can be added to each sound source individually in order to simulate auditory distance. Finally, each individual sound source can be placed at any azimuth and panned around the circle in any direction and at any speed.

Future implementations of this software will take into account more subtle aspect of auditory localisation including timbral adjustments and Doppler effects.

### E. Visualization

In a classical concert, the public ear the music but also can see the musicians, how they play or move, and which are their expressions and emotions. In EEG driven musical instrument, the musician must sit and stay immobile. We thought that adding a visual effect linked to the music could only improve the music. Therefore we study different way of showing the EEG. Finally we choose to present the signal projected on the brain cortex as explained in section V-B. When the musician is playing, every second, the recorded EEG are processed with the inverse solution approach and then averaged. An half sphere with the interpolation of the 361 solution is projected on the screen (Fig. 8).

## VII. CONCLUSION

During the workshop, two musical instruments based on biological signals were developed. One is based on EEG and the other on EMG. We chose the musical instrument approach rather than the sonification one. Furthermore all the signals were used to spatialise and visualise the sound. We had not enough time to play with the heart sound and EOG.

One of the other main achievement is the architecture we build. It enables the communication between any recording machine that can be link to a network and a musical instrument. It is based on Matlab. Therefore any specific signal processing method can be easily implemented in the architecture. Furthermore the bridge build between Matlab and Max/MSP via Open Sound Control could be easily reuse by other project. Finally, we implement basic and complex controls of the EEG. The presented algorithm obtained 75% of accuracy for the classification of hand movement.

The present paper reflects the work of a four weeks workshop. However the work did not stop with the end of the workshop. This work is in progress. Signal processing and musical instrument can be improved. First the musician needs more training. On one hand, he will get a better control of the biological signal. On the other hand he must practice the instrument to improve the mapping and learn how to play. Second other tasks than movement should be detected to give more control to the musician. Imagination of movement is one way but what about imagination of music? Finally, the closer biological signal sonification will be of the musical instrument, the closer we will be of the dream.

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APPENDIX I  
 EEG DRIVEN INSTRUMENT

Max/MSP patches for the EEG driven musical instrument:  
 Fig. 14, Fig. 15, Fig. 16.

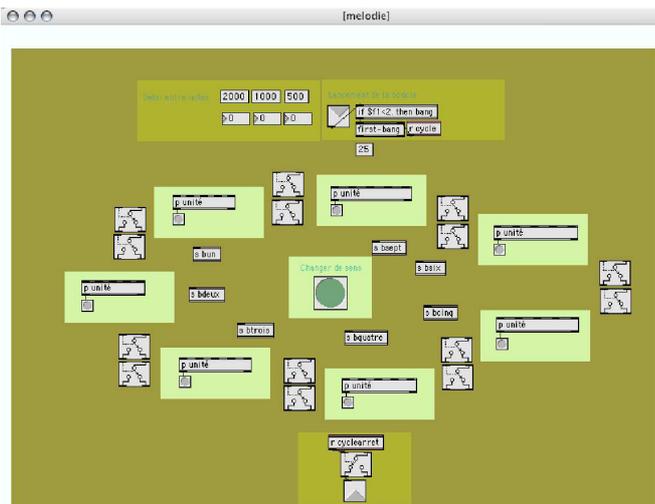


Fig. 15. Max/MSP Patch for the EEG driven musical instrument



Fig. 16. Patch of sound synthesis with Absynth

APPENDIX II  
 OPEN SOUND CONTROL

To link Matlab and Max/MSP we used two approaches. The first one is based on a C++ library, liblo (<http://plugin.org.uk/liblo/>), which implements the OpenSoundControl and UDP protocols. The library is compiled as

a Matlab plugin using the mex compiler. The file sendmat.c is an example of how to send a message from Matlab. All the functions of the OSC protocol should be accessible in this manner but only those in the example file were implemented. This has to date only been implemented under the GNU/Linux Operating System. In our case, it worked effectively in sending messages to Macintosh computers running Max/MSP under MacOS X. The second approach used the pnet TCP/UDP/IP toolbox freely available from Mathworks. In this case, packets formatted according to the OSC protocol, were written to a network socket using the pnet command. Example:

```
% head of the message
pnet(udp, 'write', '/alpha');
% mandatory zero to finish the string
pnet(udp, 'write', uint8(0));
...
% comma to start the type tag
pnet(udp, 'write', ',');
% number of float to write
pnet(udp, 'write', 'f');
...
% data to send
pnet(udp, 'write', single(data(i)), 'intel');
```

This approach worked fine for most of our various computers running different operating systems, i.e. from Matlab on Linux or Windows to Max/MSP on Macintosh. However this did not work properly when we sent data to Max/MSP running on Windows due to endian problems. The toolbox has a byte swap function to accommodate for endianness and the correct one should be chosen, (see last command of the last line of the above example.) For more details on which endianness to choose see the pnet toolbox help.

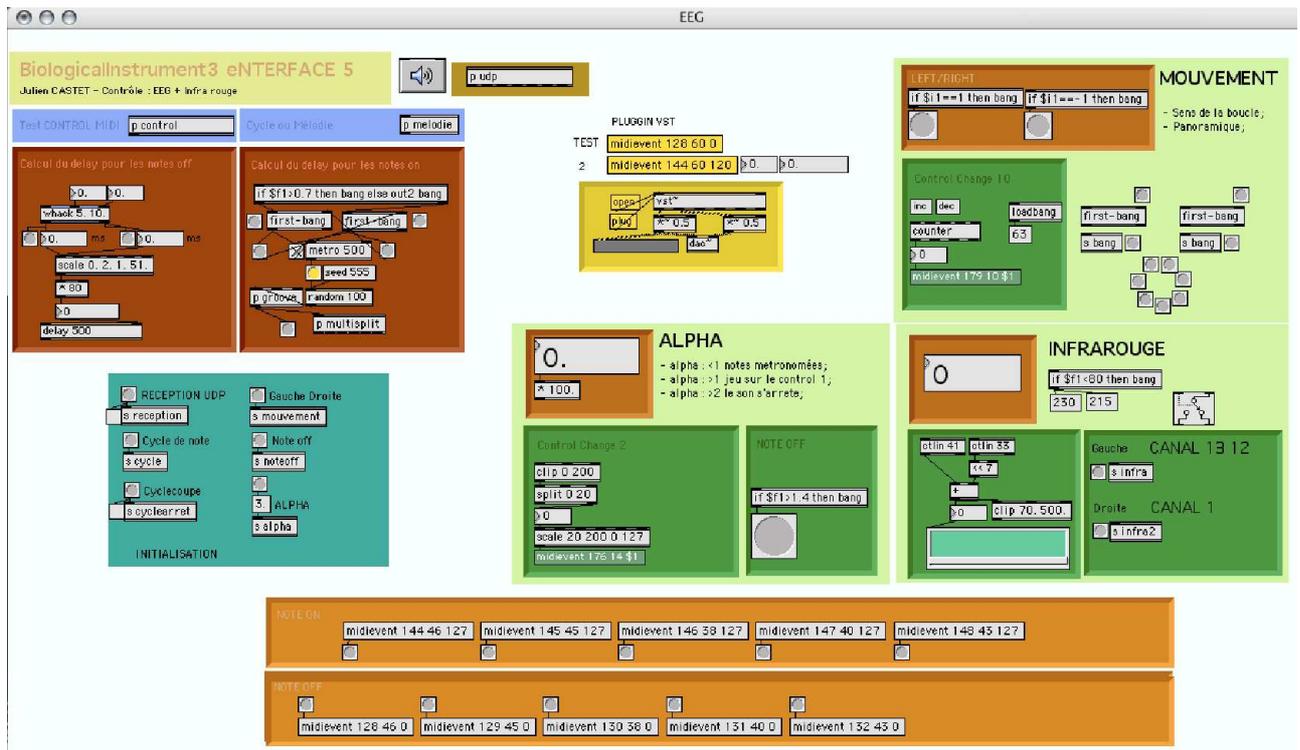


Fig. 14. Max/MSP Patch for the EEG driven musical instrument