Using physiological signals for sound creation

Jean-Julien Filatriau[1], Rémy Lehembre[1], Quentin Noirhomme[1], Cédric Simon[1],
Burak Arslan[2], Andrew Brouse[3], Julien Castet[4]

[1]Communications and Remote Sensing Lab, Université catholique de Louvain, Belgium
[2]TCTS Lab of the Faculté Polytechnique de Mons, Belgium
[3]Computer Music Research, University of Plymouth, Drake Circus, Plymouth, U.K
[4]Polytechnics National Institut of Grenoble, France

(lehembre,simon,filatriau,noirhomme)@tele.ucl.ac.be

buarslan@gsu.edu.tr,andrew.brouse@plymouth.ac.uk,julien.castet@free.fr

Abstract

Recent advances in new technologies offer a large range of innovative instruments to design and process sounds. Willing to explore new ways for music creation, specialists from the fields of brain-computer interfaces and sound synthesis worked together during the eNTERFACE05 workshop (Mons, Belgium). The aim of their work was to design an architecture of real-time sound synthesis driven by physiological signals. The following description links natural human signals to sound synthesis algorithms, thus offering rarely used pathways for music exploration. This architecture was tested during a "bio-concert" given at the end of the workshop where two musicians were using their EEG and EMG to perform a musical creation.

1. Introduction

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. Research is already being done toward integrating BCI and sound synthesis with two different approaches. The first approach tries to use the sound as a way to better understand the brain activity by mapping the data issued from physiological analysis directly to sound synthesis parameters [7] [8] [9]. This sonification process can be viewed as a translation of biological signals into sound. The second approach aims to build a musical interface where inference based on complex feature extraction enables the musician to intentionally control sound production. This is easy with electromyograms (EMG) or electrooculogram (EOG) but very difficult with electroencephalogram (EEG). In the following, we first 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.

2. System architecture overview

Our intention was to build a robust, reusable framework for biological signals capture and processing geared towards musical applications. To maintain flexibility and ensure real-time requirement, signal acquisition, processing and sound synthesis modules were performed on different physical machines linked via Ethernet. Data were acquired via custom hardware linked to a host computer running a Matlab/Simulink real-time blockset [10]. We implemented our signal processing code as a Simulink blockset using Level-2 M file S-functions with tuneable method parameters. This allowed us to dynamically adapt to the incoming signals. For the sound processing methods, we used Max-MSP programming environment dedicated to audio and multimedia real-time processing [11].
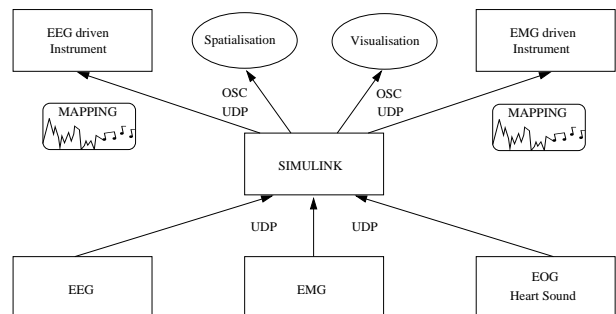

Figure 1: System architecture: measured signals from EEG and EMG recorders are sent to simulink via UDP. Data are processed in real-time with simulink and the parameters are sent to the different instruments.

Data transmission between machines was implemented using UDP/IP protocol over Ethernet. We chose this for best real-time performance. Messages were encoded thanks to the OpenSoundControl protocol (OSC) [12], which sits on top of UDP. OSC was conceived as a protocol for the real-time control of computer music synthesizers over modern heterogeneous networks. For our project, we used OSC to transfer data from Matlab (running on a PC with either Linux or Windows OS) to Macintosh computers running Max/MSP. Fig. 1 outlines main software and data exchange architecture.

3. Data Acquisition

Two types of biological signals were considered: electroencephalograms (EEG) and electromyograms (EMG)

3.1. Electroencephalograms (EEG)

Electroencephalograms data were recorded at 64 Hz on 19 channels with a DTI cap. Data were filtered between 0.5 and 30 Hz, channels were positioned following the 10-20 international system and Cz was used as reference. The subject sat in a comfortable chair and was asked to concentrate on the different tasks. The recording was done in a normal working place, e.g. a noisy room with people working, speaking and with music. The environment was not free from electrical noise as there are many computers, speakers, screen, microphones and lights around.

3.2. Electromyograms (EMG)

To record the electromyograms, 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 had 200 gain and DC-300Hz bandwidth. 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.

4. BioSignal Processing

We tested various parameter extraction techniques in search of those which could give us the most meaningful results. We focused mostly on EEG signal processing as it is the richest and most complex bio-signal. The untrained musician normally has less conscious control over brain biosignals as opposed to other biosignals and therefore sophisticated signal processing was reserved for the EEG which needed more processing to produce useful results. The data acquisition program samples blocks of EMG data, measuring arm muscles contraction, in 100 ms frames. Software then calculates the energy for EMG channels, and sends this information to the related instruments. Two kinds of EEG analysis are done (Fig. 2). The first one attempts to determine the user?s intent based on techniques recently developed in the BCI community [4]. A second approach looks at the origin of the signal and at the activation of different brain areas. The performer has less control over results in this case. In the next sections, we present more details on both of these EEG analysis approaches.

4.1. Detection of musician's 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: Ranging 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.

The wavelet transform [13] is a technique of time-frequency analysis prefectly suited for the task detection. Each task can be detected by looking at specific bandwidth on specific electrodes.

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 Daubechy 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 α 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, these are the only tasks used in this project. Two different techniques were used: Asymmetry ratio and spatial decomposition.

4.1.1. Eye blinking and α 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.

4.1.2. 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 recognize 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:

$$\Gamma_{FB} = \frac{P_{C3,FB} - P_{C4,FB}}{P_{C3,FB} + P_{C4,FB}} \tag{1}$$

where $P_{Cx,FB}$ 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.
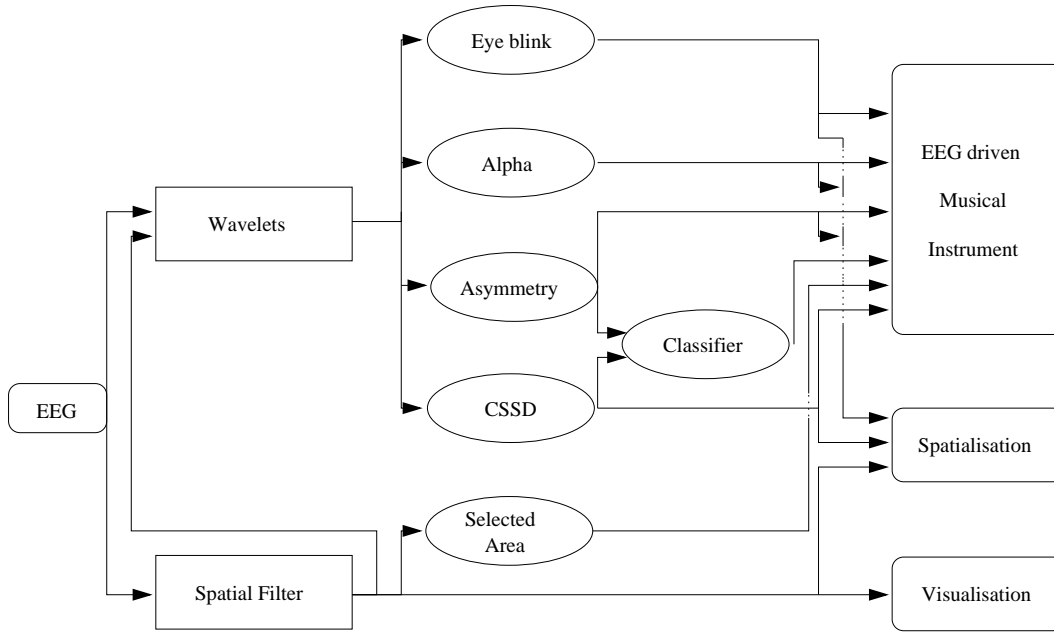
Figure 2: EEG processing, from recording (left) to play (right). Frames of EEG data are processed simultaneously with the different techniques we used. On one hand a wavelet decomposition is done and the frequency bands are sent to different sub-algorithms in order to obtain different parameters. On the other hand, the data is spatially filtered in order to obtain the EEG generators with the inverse solution. This allows us to visualize the brain activity and send parameters representing active regions.

4.1.3. Spatial decomposition

Two spatial methods have proven to be accurate: The Common Spatial Patterns (CSP) and the Common Spatial Subspace Decomposition (CSSD) [14, 15]. 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 consists in computing the autocovariance matrix for each tasks. Let's take one signal X of dimension $N \times T$ for N electrodes and T samples. Decomposing X in X_A and X_B, A and B being two different tasks, we can obtain the autocovariance matrix for each task:

$$R_A = X_A X_B^T \qquad and \qquad R_B = X_B X_B^T \qquad (2)$$

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

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

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

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

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

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

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

$$\Sigma_A = \text{diag}[\underbrace{1...1}_{ma} \underbrace{\sigma_1...\sigma_{m_c}}_{mc} \underbrace{0...0}_{mb}] \qquad (6)$$

$$\Sigma_B = \text{diag}[\underbrace{0...0}_{ma} \underbrace{\delta_1...\delta_{m_c}}_{mc} \underbrace{1...1}_{mb}] \qquad (7)$$

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

$$F_a = W U_a \qquad (8)$$

$$G_a = U_a^T P \qquad (9)$$

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:

$$\hat{X}_a = F_a G_a X \qquad (10)$$

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

4.1.4. 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 noises - which is not conducive to accurate EEG signal capture and analysis.) The asymmetry ratio gave somewhat poorer results.

4.2. 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 give us a helpful clue on the cerebral processes going on. Unfortunately, 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.

4.2.1. Forward Problem, head model and solution space

Let X be a Nx1 vector containing the recorded potential with N representing the number of electrodes. S is a Mx1 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

$$X = G\,S\,+\,n \qquad (11)$$

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 consists in calculating 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 the 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 viewing the multi-shell model as a composition of single-shells -much as Fourier uses functions as sums of sinusoid [16]. The potential v measured at electrode position r from a dipole q in position r_q is

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

λ_i and μ_i are called Berg's parameters [16]. 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 3x1 vector. Therefore each single shell potential can be computed as [17]

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

with

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

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

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

The brain source space is limited to 361 dipoles located on a 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.

4.2.2. Inverse Problem

The inverse problem can be formulated as a Bayesian inference problem [18]

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

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 a 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

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

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

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

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

$$argmax(\ln p(S|X))$$
$$= \;argmax(\ln p(X|S) + \ln p(S))$$
$$= \;argmax((X - GS)^t\,C_n^{-1}\,(X - GS) + \lambda S^t C_S S$$

where the parameter λ gives the influence of the prior information. And the solution is

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

For a full review of methods for solving the Inverse Problem see [18, 19, 20].

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-known LORETA approach [20] showed the best results on our test set. The LORETA looks for a maximally smooth solution. Therefore a laplacian is used as a prior. In

equation (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 equation (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.

5. Musical processing of biological signals

Sound synthesis 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. In literature of digital musical instruments [21], the term mapping refers to the use of real-time data received from controllers and sensors as control parameters that drive sound synthesis processes. During the eNTERFACE workshop 05, we worked on developing consistent mapping based on physiological signals in order to create biologically-driven musical instruments. For the musical processing of biological signals we chose to use Max/MSP, a widely used software programming environment optimized for flexible real-time control of music systems.

At the end of the workshop, a musical performance was presented with two bio-musicians and various equipment and technicians on stage orchestrating a live bio-music performance before a large audience. The first instrument was a midi instrument based on additive synthesis and controlled by the musicians electroencephalogram along with an infrared sensor. The second instrument, driven by electromyograms of the second bio-musician, processed recorded accordion samples using granulation and filtering effects. Furthermore, electroencephalograms signals managed the spatialized diffusion over eight loudspeakers of the sound produced by two musicians. During the months following the workshop, some experiments were pursued at Communications and Remote Sensing lab (UCL) and another instrument based on electroencephalograms were developed. We here present details of each of these instruments.

5.1. Two interfaces brain/sound

In these two instruments, we used three control parameters: right/left body movement (linked to energy in the Mu bandwidth), open/closed eyes and average brain activity (both linked to energy in the Alpha bandwidth). In order to enhance the spectator?s appreciation of the performance, we developed a quiet basic visual representation of brain activity; for this, we chose to present the signal projected on the brain cortex as explained in section 4.2. While the musician was playing, EEG data were processed once per second using the inverse solution approach and then averaged. A half sphere with the interpolation of the 361 solutions was projected on the screen.

5.1.1. First Instrument

In the first instrument, the sound synthesis is done with a plug-in from Absynth [22] which is software controlled via the MIDI protocol. The Max/MSP patch interprets the flow of EEG data to create MIDI events that control the synthesis. The synthesis algorithm is composed of three oscillators, three Low Frequency Oscillators, and three notch filters. Sequences of MIDI notes are triggered by the opening of the eyes and permutated according to the right/left body movement. The succession of notes is subject to randomized variations of the notes duration and the delta time between each note. An additional infrared sensor gives an instantaneous control on the frequencies of the LFO.

5.1.2. Second Instrument

In the second instrument, the synthesis is achieved by Quick Time synthesizer driven in the Max-MSP patch. The patch also used the scansynth object developed by Couturier [23] and other externals provided in the Real Time Composition library [24] allowing to generate harmonized melodies. Alpha and Beta bandwidth are used to both modulate loudness, rhythm and pitch range of the melody and trigger sound events when thresholds are crossed. The opening of the eyes allows the musician to change the Quick Time instrument whereas the panning between left and right speakers is linked to the right/left body movement by the way of the energy in the Mu bandwidth.

5.1.3. Results

The aim of this work was to create an instrument controlled by electroencephalogram signals. While interaction between music and musician usually rely on gestures, there is no physical interaction here. This implies some lack of control in the synthesis process for the musician, though some parameters can be intentionally controlled, with eyes opening especially. By this way we are here at the boundary between two approaches, the sonification approach, where the sound is just a translation of input data without intentional human control, and the musical instrument approach, that relies on a high level of interaction between the musician and the synthesis process. Furthermore, the relationship between the musician and the music acts in two directions: the musician interacts with sound production by means of his EEGs but the produced sound also interacts via a feedback influence on the mental state of the musician. Future work will turn toward the biofeedback potential for influencing sound.

5.2. EMG-controlled granular synthesis

In the second instrument, sound synthesis is based on the real-time granulation and filtering of recorded accordion samples. During the demonstration, the musician starts his performance by playing and recording a few seconds of accordion, which he will then process in real-time. Sound processing was controlled by means of data extracted from electromyograms (EMG) measuring muscle contractions in both arms of the musician.

5.2.1. Granulation

Granulation techniques split an original sound into very small acoustic events called grains and reproduce them in high densities of several hundred or thousand grains per second [25]. In our instrument, three granulation parameters were driven by the performer: the grain size, the pitch shifting, and the pitch shifting variation. In terms of mapping, the performer selected the synthesis parameter he wanted to vary thanks to an additional midi foot controller and this parameter was then modulated according to the contraction of his arm muscles, measured as electromyograms. The contraction of left arm muscles allowed choosing either to increase or decrease the selected parameter, whereas the variation of the parameters were directly linked to right arm muscle tension.

In addition to granulation, a flanging effect was implemented in our instrument. Flanging is created by mixing a sig-

nal with a slightly delayed copy of itself, where the length of the delay, less than 10 ms, is constantly changing. The performer had the ability to both modulate flanging parameters and control the balance between dry and wet sounds via his arm muscle contractions.

5.2.2. Results

Peculiar sounds, near or far from original accordion timbres, 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 filtering parameters configurations. As with any traditional musical instrument, the first thing going forward will be to practice the instrument in order to properly learn it. These training sessions will aim to improve the mapping between sound parameters and gestures. However, a major improvement to enhance the interaction between musician and instrument would be to add electromyograms measuring muscles contraction in other body parts (legs, shoulders, neck) and map these data to new kinds of sound processing.

6. Conclusion

This paper presents the result of a collaborative work held during the eNTERFACE 05 Summer Workshop (Mons, Belgium), where specialists in biomedical signal processing and sound synthesis fields shared their knowledge over four weeks. The aim of the project was to develop an interface between these two fields. Thus we created several digital musical instruments driven by electroencephalograms and electromyograms signals and a live performance was presented on stage at the end of the workshop. For this, we built an efficient architecture for real-time communication between data acquisition, biomedical signal processing and sound synthesis modules. This modular architecture will enable to easily pursue such experiments in the future : indeed, signal processing methods and mapping strategies could be improved in order to make the system more robust and to enhance the interaction between the musician and the instruments. Developing an advanced visual feedback that translates brain activity also seems to be a very interesting improvement. These are some of the different pathways that we will explore during the second eNTERFACE workshop in Summer 2006 (Dubrovnik, Croatia).

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