EMOTIVE CINEMA

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ABSTRACT

New affordable electroencephalographic (EEG) devices dedicated to the game industry have recently appeared on the market. Consequently, more and more artists inspired by these promising technologies imagine the possibility to directly integrate human emotions in their performance through measurement of the brain waves. The main goal of this project is to assess the possibility to make "Emotive cinema" with consumer grade EEG headsets. In such approach, the story of a movie would directly be influenced by the emotional state of the audience. In this report, we describe a first attempt to detect the valence (positive or negative value) of emotions provoked by different video excerpts amongst several spectators seated in a realistic movie theater, on the basis of their EEG signals only. Preliminary results obtained indicate that positively and negatively valenced video excerpts may be discriminated in the training data set but not on an independent data set. These results are extensively discussed in order to describe further studies and developments that should be made in the future.

KEYWORDS

Electroencephalography, emotion, cinema

1. INTRODUCTION

Luigi Galvani (1737-1798) is a pioneer in the field of electricity and, in particular, its relationship with the nervous system. At the end of the 18th century, he conducted experiments with frogs and static electricity and demonstrated that by stimulating the sciatic nerve of the frog with electricity, the muscles connected to this nerve contracted. This discovery was a first milestone in the study of bioelectricity.

Much later, at the beginning of the twentieth century, Willem Einthoven was the first to invent a machine able to record the electrocardiogram (1903). At the epoch, it was already known that the beating of the heart produced electrical currents, but the instruments of the time could not accurately measure this phenomenon without placing electrodes directly on the heart. Einthoven was awarded the Nobel prize of medicine for his machine in 1924.

The same year, Hans Berger discovered the electrical activity generated by the brain. He recorded for the first time a human electroencephalogram (EEG). The signals he obtained in a non-invasive way were called "alpha waves", as they were the first to be detected. Berger showed that these signals were similar to a sinusoidal reference oscillating at 10 Hz. He published his discovery only in 1929 and was nominated for the Nobel Prize in 1936.

Since then, other kinds of brain waves have been found. These have been divided in several characteristic frequency bands: δ (waves oscillating below 4 Hz), θ (from 4 to 8 Hz), α (from 8 to 13 Hz), β (from 13 to 30 Hz), and γ (above 30 Hz). Each EEG band has its own typical localization on the scalp and help physicians to detect different neural pathologies. Electroencephalography is also used – in conjunction with other biosignals – to study sleep disorders.

More recently, EEG signals have been exploited to develop Brain-Computer Interfaces (BCI). This kind of interface allows disabled people to communicate [2], control computers [7] and drive robotic [3] or prosthetic devices [4] via the power of their brain only. In short, BCI are developed according to the following scheme: different intentions or mental events have to be elicited in the brain of the user. Brain activity is then recorded (generally using EEG, which is a non-invasive technology); signals are cleaned, in order to get rid of the different artifacts (eye movements, muscle activities, . . .) polluting the raw data; relevant features are then extracted and injected in a pattern recognition algorithm. Finally, according to the classification results, pre-defined commands are sent to the computer or the device to be controlled (cf. Figure 1). In practice, one may activate high level commands like "go straightforward", "turn left", "turn right" in the case of a motorized wheelchair or different keyboard letters in the case of a text-speller application. The user is then provided with a feedback from the computer or the device, in order to understand which command or action was detected by the system.

With the recent advent of affordable electroencephalographic devices on the market, Brain-Computer Interfaces are becoming available to a broad public. These consumer grade headsets are primarily dedicated to provide a new control in video games but other applications can be imagined. Artists, for instance, are definitely willing to use these cheap headsets in order to integrate brain waves in their performances. In this context, we present a preliminary study to evaluate the possibility to integrate brain waves in the control of a movie, a concept called "Emotive Cinema" in the following of this paper. Section 2 describes the objectives defined in this numediart project. The evaluation of the quality of the Emotiv EPOC headset (http://www.emotiv.com) and the resolution of different technical difficulties are given in section 3. The experimental approach and preliminary results related to emotion recognition using EEG signals are presented in section 4. The experimental "Emotive Cinema" setup is described in section 5. A discussion of this study and future work that could be envisaged is then given before final conclusions.

2. OBJECTIVES AND TECHNICAL CHALLENGES

This numediart project was set up on the basis of a specific demand from an artist team desiring to transpose the gamebook literary genre to the world of cinema. Ultimately, the idea is to influence the story of a film taking into account the emotional state of the audience. In a first step, the film makers would be interested to have the possibility to add and control special cinema effects using affective information coming from the audience. The re-

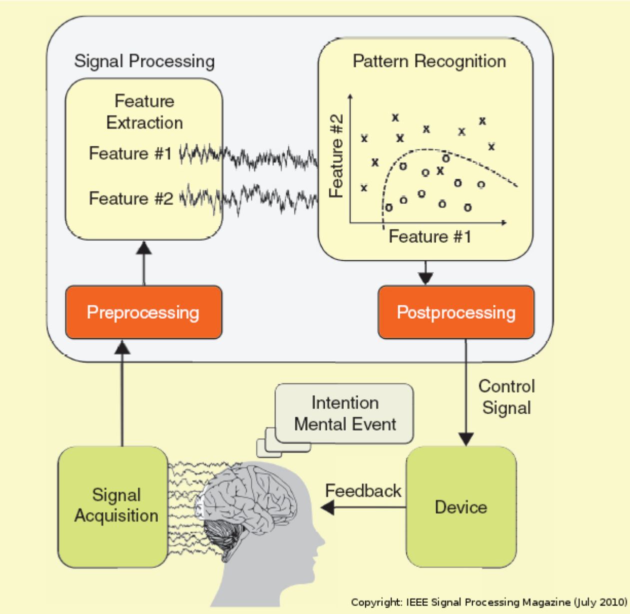

Figure 1: *A Brain-Computer Interface is able to discriminate different mental events elicited in the brain of the user. Brain activity is generally acquired using EEG technology. A pre-processing phase is applied to the raw signals in order to clean them from different artifacts due for instance to eye movements or muscle activity. Afterwards, some relevant features are extracted and classified to determine the mental event produced in the brain of the user. Finally, the identified signal is associated to a specific action or pre-defined command in order to control the computer or a given electrical device.*

alization of such interface raises multiple questions and requires practical problems to be solved. The principal issues identified at the beginning of this project were the following ones:

1. Is it possible to extract information related to the affective state of the audience analysing the EEG signals of the spectators, in particular with Emotiv headsets ?
2. Is it possible to connect and synchronize several headsets and thereby develop a technical solution to experiment further ?
3. To what extent large amounts of data can be sent to the computer ? How many headsets can be connected to the same computer ?
4. Movements of people can be captured by the Emotiv headsets, through the electrical activity of the muscles. Is this considered as problematic in the detection of the affective state of the spectators ? Does one have to integrate artifact removal techniques to limit the interferences ?

3. THE EMOTIV EPOC HEADSET

In this section, we give an evaluation of the performance of the Emotiv EPOC headset used in the context of BCI and we explain the resolution of different technical difficulties encountered when trying to connect several headsets to one machine running the Openvibe software.

3.1. Hardware quality assessment

In a previous work, TCTS lab had already assessed the quality of Emotiv EPOC headsets, by comparing their performance in the framework of a P300-based brain-computer interface with the performance reached using a medical EEG system (on the basis of the same electrode configuration, of course) [1]. Figure 2 illustrates that, albeit giving worse results than those obtained with the medical system, Emotiv EPOC headsets are usable for BCI applications.

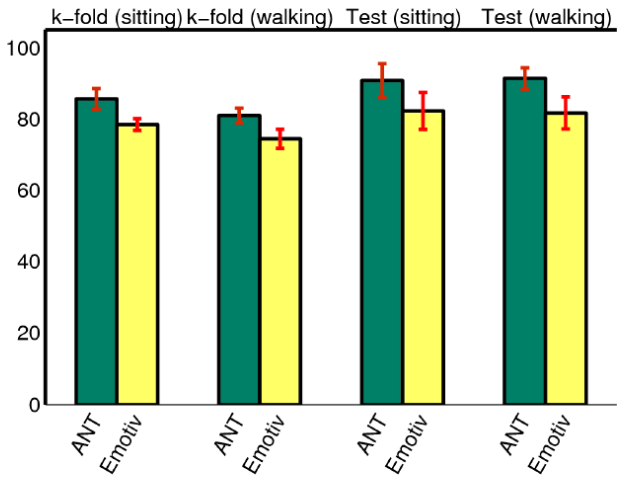

Figure 2: *This Figure reports average and standard error values of classification rates obtained with a medical EEG system (ANT) and the Emotiv EPOC headsets under sitting and walking conditions. The chance level is 25 %. This illustrates that Emotiv headsets are usable for this kind of BCI (Figure adapted from [1]).*

3.2. Interconnectivity issue

The framework chosen to develop the "Emotive Cinema" experimental setup is Openvibe (`http://openvibe.inria.fr`), an open source software dedicated to Brain-Computer Interfaces and real time neurosciences. Indeed, to our knowledge, this is the only software able to manage the synchronization of several acquisition systems (i.e. several headsets in our case). In practice, we found that Openvibe did not correctly receive the signals from two or more Emotiv headsets. In fact, signals from Emotiv headsets are transmitted to the computer without any wire. USB dongles (one per headset) receive the encrypted raw data that must subsequently be decoded using the licensed Emotiv SDK software. Actually, the signals obtained in Openvibe were completely messed up, as if Openvibe tried to listen to all USB dongles at the same time. We found that the Openvibe driver for the Emotiv EPOC headset was correctly written on the basis of the documentation given with the Emotiv Research Edition SDK_v1.0.0.4-PREMIUM. We solved the problem by using the Emotiv Research Edition SDK_v1.0.0.5-PREMIUM and by modifying the Openvibe driver in order to make sure that the origin of each data packet was correctly identified.

4. EMOTION RECOGNITION USING EEG

This section is dedicated to the description of our experimental work aiming at assessing the possibility to discriminate basic emotions with Emotiv EPOC headsets. First, we will explain a very simple model used to characterize emotions. The questionnaire used to determine which emotions were felt after viewing a given picture or video excerpt will then be presented. Finally, we will describe our experimental approach and show the preliminary results obtained.

4.1. Emotion modelling and Self-Assesment Manikin (SAM)

In psychology, one typical way to characterize human emotions consists in projecting them into a 3-dimensional space [5]. The first axis of this space is *valence*, which represents the positive, neutral or negative aspect of the emotion. *Intensity* of the emotion is evaluated on the second axis. It represents the arousal felt during a given stimulus. Finally, *dominance* indicates to what extent the emotion felt was controllable or not. For instance, breaking into tears or hard laughing are examples of uncontrollable emotions, characterized by a small dominance value. In certain cases, limiting the decomposition to 2 dimensions (intensity and valence) is considered as sufficient. In this particular way of characterizing emotions, *well-being* would be represented by a positive valence and a small intensity value, *joy* by positive valence and high intensity, *sadness* by a negative valence and small intensity and *anger* by a negative valence and high intensity.

As emotions are personal feelings that can not be acurately measured by specific apparatus, the standard way to determine them consists in asking subjects to fill in a questionnaire. The Self-Assesment Manikin (SAM) questionnaire [6] is a non-verbal pictorial assessment technique which divides the valence, intensity and dominance axes in five intervals each, as represented on Figure 3. The SAM ranges from a smiling, happy figure to a frowning, unhappy figure when representing the pleasure dimension, and ranges from an excited, wide-eyed figure to a relaxed, sleepy figure for the arousal dimension. The dominance dimension represents changes in control with changes in the size of SAM: a large figure indicates maximum control in the situation. During an experiment, each subject is asked to put an 'x' on the three axes (each divided in 5 intervals) in order to describe as best as possible the emotion he/she felt in front of a given stimulus. The results can be converted to numerical values afterwards.

4.2. Experimental approach

4.2.1. Protocol

The experiment conducted in this project consisted in presenting five video excerpts of 2 or 3 minutes each to different subjects wearing an Emotiv EPOC headset. The objective was to provoke a large variety of emotions by the subjects, by successively presenting them quiet landscapes of paradisiac islands, a depressive man, a war scene, an excerpt of a one-man show of a french humorist and finally the recording of an impressive electronic cellos duo (cf. top of Figure 4). After watching each short movie, the three participants were asked to fill in a SAM questionnaire. The average results of the three questionnaires are shown at the bottom of Figure 4. One can observe that all the regions of the intensity-valence plane are sampled by the 5 chosen video excerpts. EEG signals were stored on disk for offline analysis.

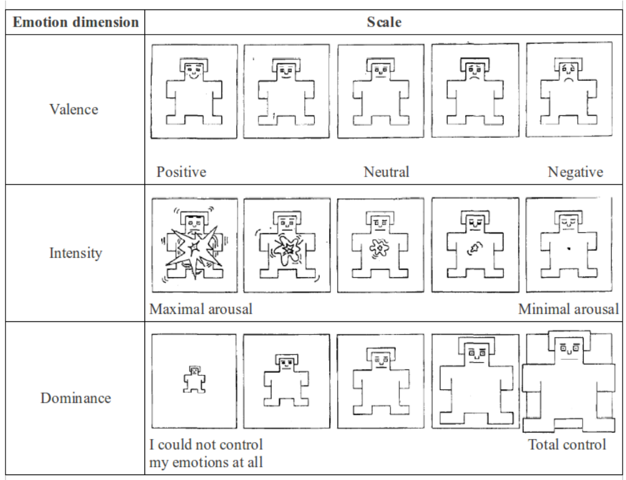

Figure 3: *The five scale Self-Assesment Manikin (SAM). The subject is asked to put an 'x' on each axis of the SAM in order to describe as best as possible the emotion he/she felt in front of a given stimulus. The results can be converted to numerical values afterwards.*

4.2.2. Asymmetry in frontal brain activity and emotion valence

Our analysis is based on the results published by Schmidt *et al.* [6] who showed that:

"... positively valenced musical excerpts elicited greater relative left frontal EEG activity, whereas negatively valenced musical excerpts elicited greater relative right frontal EEG activity ... In addition, positively valenced (i.e., joy and happy) musical excerpts elicited significantly less frontal EEG power (i.e., more activity) compared with negatively valenced (i.e., fear and sad) musical excerpts, and there was significantly less frontal EEG power (i.e., more activity) in the left compared with the right hemisphere across valence."

In other words (cf. Figure 5), measuring the asymmetry of the frontal brain activity would enable to discriminate the valence (+ or -) of emotions, at least from the musical point of view. Several other publications in emotion recognition using electroencephalography give similar results. In very brief outline, the analysis scheme is generally about the same in these studies: 1) compute the power of EEG in different frequency bands, 2) combine these values in some way, 3) use different classifiers and 4) evaluate the results.

4.2.3. Signal processing

We decided to select frontal electrodes of the Emotiv headset, according to the prescription given in [6]. To compare the activity of the left and right brain hemispheres, we computed the difference between the EEG signals measured by symetric electrodes, namely AF3-AF4, F3-F4, F7-F8, FC5-FC6, as defined in the international 10/20 system. Signals were then band-pass filtered with a 4th order Butterworth filter whose low and high cut frequencies were respectively set to 8 and 12 Hz for the alpha band, 12 and 30 Hz for the beta band, 30 and 60 Hz for the gamma band. The sampling frequency of the Emotiv headset is fixed to 128 Hz. No additional artifact cleaning algorithm was used.

EEG data were divided in overlapping windows of 4 seconds

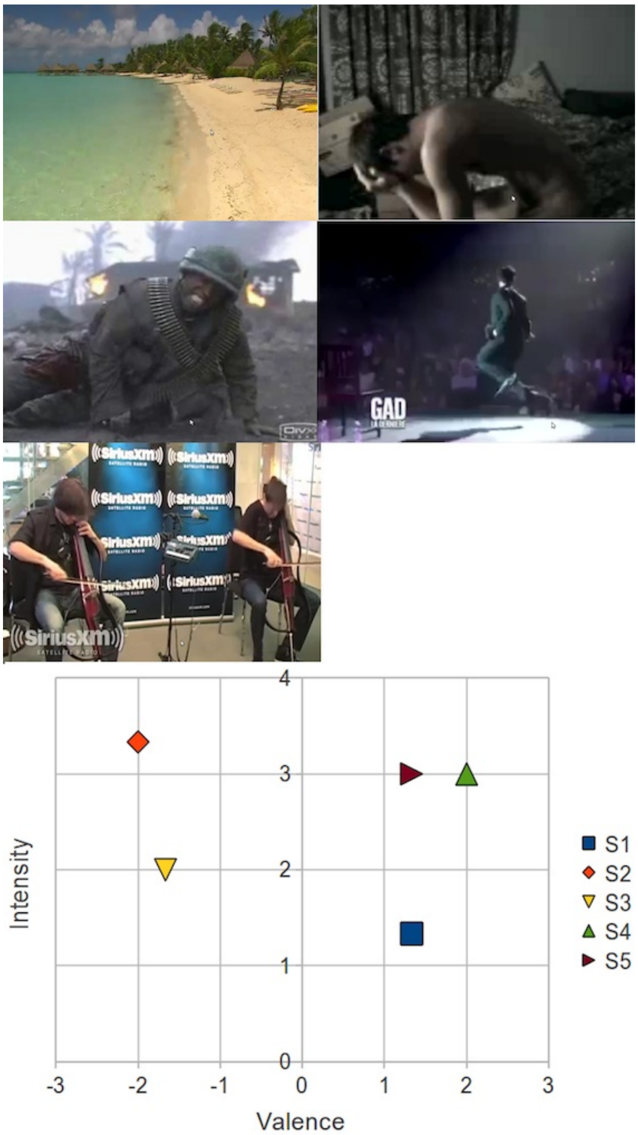

Figure 4: *Top: screen captures of the 5 video excerpts chosen for our experiment. Stimulus S1 presented quiet landscapes of paradisiac islands, stimulus S2 exhibited a depressive man, stimulus S3 a war scene, stimulus S4 was an excerpt of a one-man show of a french humorist and stimulus S5 was the recording of an impressive electronic cellos duo. These videos were found on the youtube website. Bottom: the average SAM results indicate that all the regions of the intensity-valence plane are sampled by the 5 chosen video excerpts.*

duration every 0.5 second. Thus, two times per second, 12 features (i.e. 3 powers alpha, beta and gamma for the 4 frontal electrode differences) were sent to a simple Linear Discriminant Analysis (LDA) classifier. This classifier was trained using one minute of stimulus S1 (the movie with paradisiac islands) in order to learn the EEG characteristics of a positively valenced emotion and one minute of stimulus S2 (the movie with the depressive man) in order to learn a negatively valenced emotion. The Openvibe software was used to realize this signal processing and classification

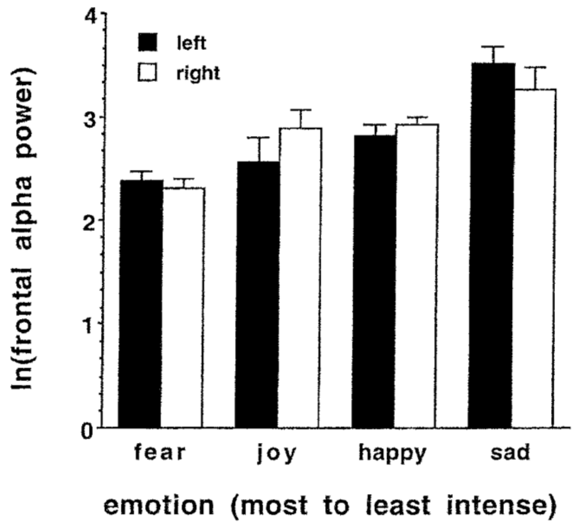

Figure 5: *Differences among four musical excerpts on left and right frontal EEG alpha power (note that EEG power is inversely related to activity, thus lower power reflects more activity). Error bars represent the standard error of the mean (Figure from [6]).*

task. Training was done using a 12-fold procedure. A k-fold test generally allows better classification rates. The idea is to divide the set of feature vectors in a number of partitions. The classification algorithm is trained on some of the partitions and its accuracy is tested on the others. The classifier with the best results is then selected as the trained classifier.

4.3. Preliminary results

The performances of the LDA classifier after the training procedure are presented in Table 1.

Subject	12-fold (%)	Sigma (%)
1	0.94	0.04
2	0.99	0.01
3	0.91	0.06

Table 1: *Performance of the LDA classifier for the training data set obtained for each subject. Good results indicate the possibility to discriminate EEG signals related to stimuli S1 and S2. Training was done using a 12-fold procedure in order to improve the determination of classification rates.*

Good results demonstrate the possibility to discriminate EEG signals related to stimuli S1 and S2 (in the training data set), on the basis of the signal processing described in previous section. However, these encouraging results must be correctly validated with a test dataset before making any valid conclusion. We thus computed the output of the trained LDA classifier when it was fed with EEG data (processed as described above) recorded during the 5 different movies (i.e. EEG data not exploited during the training phase). Figure 6 shows the LDA classifier results as a function of time. In this plot, the blue points indicate the valence result given by the LDA classifier. Positive (negative) valence results are depicted by the value +1 (-1). With a perfect classifier, we should always get +1 values for positively valenced movies (i.e. stimuli

1, 4 and 5) and -1 values for negatively valenced movies (i.e. for stimuli 2 and 3). In practice, one observe that this is not the case. On average, the classifier gives the correct answer only about half of the time. This is actually the chance level for a two-state decision. Notice however that during the entire stimulus 1, the LDA gives the correct answer.

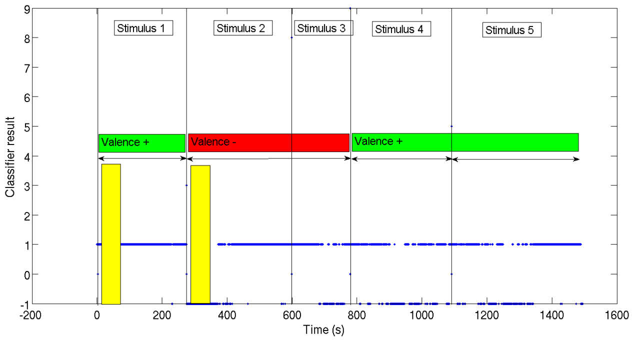

Figure 6: *LDA classifier results as a function of time. Positive and negative valence results are respectively depicted by +1 and -1 blue points. Stimuli 1, 4 and 5 were positively valenced whereas stimuli 2 and 3 were negatively valenced. Yellow rectangles indicate the training data set. In this configuration, the classifier gives the correct answer only about half of the time. This is actually the chance level for a two-state classifier.*

5. EMOTIVE CINEMA SETUP

In this section, we give an overview of our experimental "Emotive Cinema" setup, regardless of the preliminary results obtained and described above. Next section will be dedicated to the discussion of results and improvements to be brought to the setup.

5.1. General scheme

In our experimental "Emotive Cinema" setup, three Emotiv headsets are sending raw EEG data to a Windows PC, via three corresponding USB dongles. Acquired raw data are processed in real time in the Openvibe software following the pipeline described in section 4.2.3. Openvibe communicates the LDA decisions via a Virtual Reality Peripheral Network (VRPN) client/server (`http://www.cs.unc.edu/Research/vrpn/`) in which we have incorporated Oscpack (`http://www.rossbencina.com/code/oscpack`) functionalities in order to send OSC packets through the local network. These packets are received by an Apple machine running MaxMSP software, which plays the cinema with added special effects. In practice, the Openvibe scenario we used is shown on Figure 8 (this represents the data processing for one spectator only).

5.2. Parameters used to control cinema effects

The philosophy adopted in this project consisted in the detection of valence (+ or -) of emotion felt by spectators watching different movie excerpts in order to control diverse cinema effects. This is a simple 2-class detection problem for which we used an LDA classifier. Mathematically, the LDA gives, once trained, the position of an hyperplane which optimizes the classification performance.

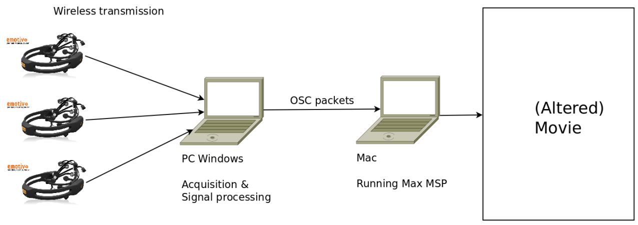

Figure 7: *Our experimental "Emotive Cinema" setup. A windows machine collects raw data from Emotiv EPOC headsets and processes them through the Openvibe software. Openvibe communicates the LDA decisions via the VRPN client/server which can send OSC packets through the local network. These packets are received by an Apple machine running MaxMSP software, which plays the cinema with added special effects.*

The distance separating each sample from that hyperplane is computed and the sign of this value indicates to which class the sample belongs (cf. Figure 9). Instead of using this categorical information to control cinema effects, we decided to use the distance to hyperplane in order to control cinema effects. Several reasons support this decision:

First, this is a more refined information than a simple categorical value. Indeed, small distances (in absolute values) indicate that the samples are close to the boundary. Hence, their distinction is less clearly established than for samples far away from the hyperplane. Using the distance allows in some way to introduce the notion of confidence in the classification.

Second, the distance is fluctuating on a certain range of values, instead of the discrete [-1,+1] interval. It thus gives many more possibilities to modulate and control cinema effects.

Third, we think that these values are intrinsically more normalized across people than EEG band power values. It is thus more legitimate to use these values in the case where a comparison between different spectators is desired.

5.3. Max MSP interface

In our experimental "Emotive Cinema" setup, the control of simple cinema effects was carried out with a Max MSP interface (`http://cycling74.com`). Max is a platform for real-time signal processing, which allows both fast prototyping by using visual programming with libraries supported by a large community and flexibility by the possibility to build additional blocks if needed.

The Max MSP interface collects the OSC packets sent by the VRPN server. These packets contain, for each Emotiv EPOC headset, the alpha, beta and gamma band powers as well as an estimation of the valence of the emotion (i.e. the distance to LDA hyperplane) felt by the user. All these values can be plotted in real time for visual inspection (cf. Figure 10).

As a very simple cinema effect, we used the value of the valence to modify the brightness of the video (the more positive the valence, the brighter the image). The interface allows the estimation of the valence synchronized with the video to be saved on disk as a Max MSP Binary File. This option makes it possible to build a database useful for long term analyses.

Figure 11 shows an effect obtained with three users. Frontal brain activity of each user influences the brightness of one part of the screen. Of course, these simple illustrations are only given as basic examples of "artistic" possibilities. Other feedbacks are

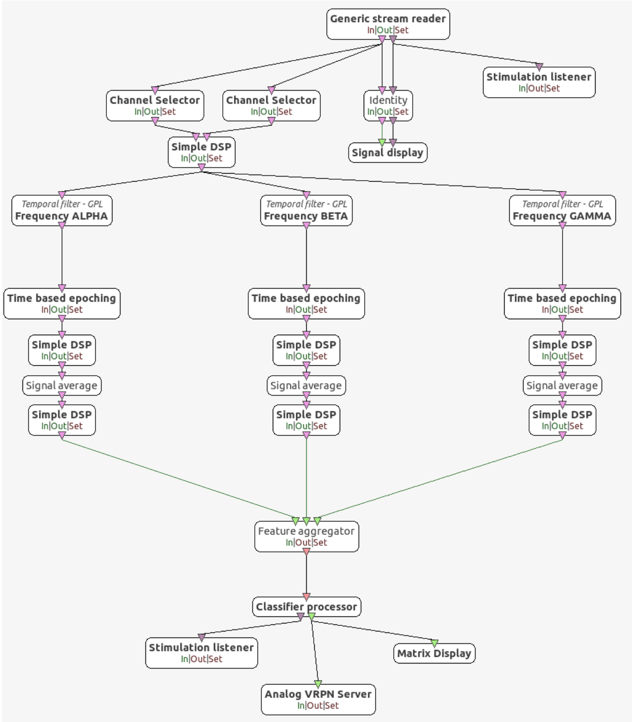

Figure 8: *Openvibe integrates an easy to use graphical language which allows to quickly program a simple BCI. In this scenario, one selects frontal electrodes of the Emotiv headset. The difference between symetric electrodes is computed. Alpha, beta and gamma powers are computed in windows of 4 seconds duration overlapping every 0.5 second. A simple LDA classifier is trained to discriminate positively and negatively valenced emotions. The distance to the LDA hyperplane is sent under OSC packets through the local network via a VRPN modified in order to integrate Osc-pack functionalities.*

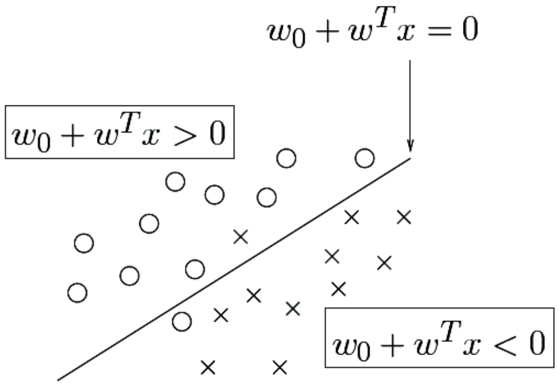

Figure 9: *During the training phase of the LDA classifier, the position of the hyperplane used to separate the two classes samples is modified in order to optimize the classification performance. Once trained, the distance separating each sample from the hyperplane can be computed. The sign of this value indicates to which class the sample belongs.*

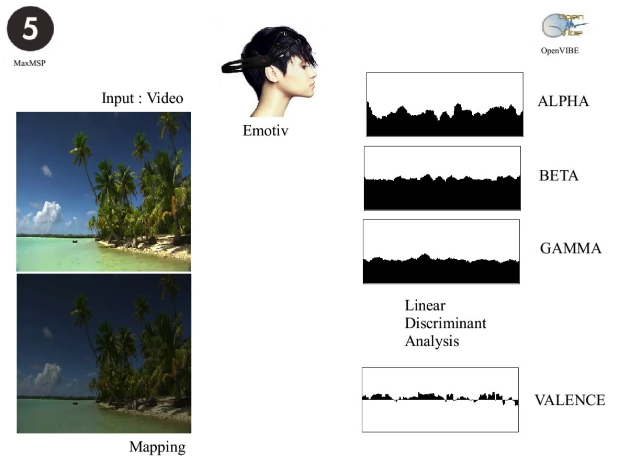

Figure 10: *Different values are plotted in this Max MSP interface: the alpha, beta and gamma EEG band powers (for a single user), as well as an estimation of the valence of his/her emotion. On the left, both the original and altered movies are shown. In this case, brightness of the movie is modified according to the valence estimated value (simple linear mapping).*

possible and it is up to the film makers to develop this aspect. For instance, the valence values of all the users could be compared. If small (large) discrepancies are found, a harmonious (dissonant) sound could be produced, as auditory feedback. Another effect could also link the light intensity of the room with the estimation of the valence.

6. DISCUSSION AND FUTURE WORK

In this section, the preliminary results presented in section 4.3 are discussed and a few precise functionalities to be added to the experimental setup are given.

6.1. About the preliminary results

Due to the time-scale of the project and the numerous practical problems encoutered, much work remains to be done in order to transform "Emotive Cinema" into a workable concept. The very preliminary results obtained are encouraging (excellent classification results in the training phase) and frustrating (chance level results in the testing phase) at the same time. In a most pessimistic and sarcastic way, people could say that this setup is finally a complicated way to generate random numbers. In reality, with such small statistics, we are not able to draw any valid conclusion at this point. Major technical problems have been solved and a research framework has been developed. New experiments should start now, with the aim of elucidating the following points:

1. Is our experimental protocol valid ? More precisely, is it legitimate to use a SAM questionnaire to characterize one global emotion felt during a movie of several minutes duration ? It seems reasonable to think that emotions will fluctuate on such time scales. Considering this, the way we are computing the classifier performance becomes highly questionable.
2. Do EEG artifacts correction algorithms improve the performances ? Same question focusing on alpha band only.

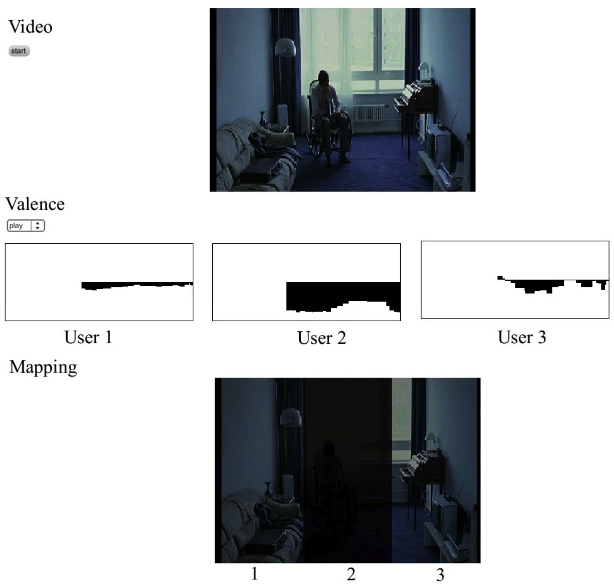

Figure 11: *Frontal brain activity of each user influences the brightness of one part of the screen.*

3. Instead of using only frontal electrodes, could an elaborated spatial filter (CSP) help in this task ?
4. Would it be beneficial to combine two LDA classifiers, i.e. one dedicated to the discrimination of valence and the other one dedicated to the intensity of emotions ?
5. We trained the classifier using stimuli S1 and S2, which are differing on both axes of the valence-intensity plane. Is this problematic ? Would it be better to use two stimuli varying only in valence (and not in intensity) in the training data set ?
6. Is there a better strategy than the one described in Schmidt *et al.* [6] and on which we based our investigations ?

Other approaches, fundamentally different, could also be envisaged for the development of future "emotive cinema" application. A classifier could be trained to recognize a relaxed/focused state, asking the subjects to intentionally place themselves in such emotional states. One could also compare emotion detection results obtained with the licensed Emotiv software.

6.2. About the experimental setup

From a technical point of view, we consider it would be helpful to develop new functionalities to the experimental setup like for instance a new box in openvibe allowing to directly send data in OSC packets. Also, a script generating automatically the good Openvibe scenario for different headsets numbers would facilitate experiments. Finally, sporadic problems of loss of communication between the headsets and the Windows machine should be assessed.

7. CONCLUSIONS

Nowadays, emotion recognition using electroencephalography is a hot research topic. Many publications are being produced on the subject, with the aim of developing new human machine interfaces. With the advent of cheap EEG headsets on the market, the number of artists desiring to integrate brain waves in their performances has dramatically increased. This `numediart` project was set up on the basis of a specific demand from a team of film makers willing to add and control special cinema effects using affective information coming from the audience.

In this project, we have developed and provided a functional solution of "Emotive Cinema", incorporated in a competitive and open-source BCI development framework. We have shown that several [1] Emotiv headsets could be used to control in real time simple cinema effects. The control of these effects is done using an estimation of the valence of the emotions felt by three different spectators. Our preliminary results suggest that the robustness of this estimation is weak but this conclusion should be considered as preliminary due to the small statistics of data. Moreover, the intrinsic complexity of measuring the evolution of various emotions felt by spectators on a several minutes duration video excerpt further complicates the interpretation of these results.

These different considerations demonstrate the need for further developments in this exciting research area. We are convinced that answering the different questions raised at the end of this `numediart` project would require a long-term research effort. We consider that the time where emotions will be interpreted using EEG signals may still be far ahead of us. However, artistic performance can definitely be realized using such biosignals provided no shortcut is taken in the interpretation of emotions with the experimental setup presented here.

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