Short Paper

Evaluation and Comparison of a Multimodal Combination of BCI Paradigms and Eye Tracking With Affordable Consumer-Grade Hardware in a Gaming Context

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***Abstract*—This paper evaluates the usability and efficiency of three multimodal combinations of brain–computer interface (BCI) and eye tracking in the context of a simple puzzle game involving tile selection and rotations using affordable consumer-grade hardware. It presents preliminary results indicating that the BCI interaction is interesting but very tiring and imprecise, and may be better suited as an optional and complementary modality to other interaction techniques.**

***Index Terms*—Brain–computer interfaces (BCIs), eye tracking, multimodal interaction.**

I. Introduction

BRAIN–COMPUTER INTERFACES (BCIs) first appeared in the 1970s and required brain implants. Thanks to electroencephalography (EEG), they have become adapted for more general-purpose applications. In addition to expensive high-quality medical devices, some affordable EEG headsets, such as Emotiv Epoc [13], claim to allow for the use of BCIs in mainstream applications such as gaming. Because they are very easy to use (wireless, no gel), this kind of device has the potential to fit the basic requirements of gaming experience for nondisabled people. However, BCI systems still suffer [7] from many issues (high error rates, insufficient bandwidth, long learning phases), and these problems are exacerbated with consumer-grade hardware. It is becoming even more paramount to find strategies and approaches to mitigate these issues.

An interesting approach appears to be the use of BCIs in multimodal interaction systems to achieve either redundancy or complementarity (in terms of CARE properties [14]).

Among all the possible modalities that could be used in conjunction with BCIs, we have chosen to start with a modality that does not involve any physical contact, that of eye tracking [16]. The choice of eye tracking seemed pertinent as not only has it been used for over 20 years in human–computer interaction (HCI) [1], but it also appears fairly robust. However, most of all, *a priori* it exhibits properties very complementary to BCIs. Indeed, eye tracking is naturally adapted to selection tasks, while BCIs are more adapted for triggering actions.

In this context, we performed an experiment in order to evaluate the effects and performance of multimodal combinations of BCIs and eye tracking using affordable consumer-grade hardware.

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First, we briefly introduce the topic and review related research, and then present the game we developed, as well as its different modality combinations. Then, we detail the objectives and methods of our evaluation and experiments, ultimately analyzing our preliminary results.

II. Background

A. Eye Tracking

An eye tracker, as the name suggests, is a device that records the tracking of the gaze coordinates on the screen. While there is a long history of using eye tracking in HCI [1], its use for interaction with games is recent [9].

B. Brain–Computer Interfaces

There are three BCI paradigms [12]: 1) active (control through direct feedback); 2) reactive (response to stimuli); and 3) passive (no voluntary control). Here, we are interested in using a BCI modality for triggering actions; therefore, we only use the active and reactive paradigms. More specifically, we have decided to use two of the methods that are suited for this task: steady-state visual evoked potentials (SSVEP) [5] and Graz motor imagery [6]. SSVEP is based on the evocation of potentials at a certain frequency, stimulated by a flickering target at that same frequency, and as such is a reactive paradigm. As for Graz, it is based on imagined hand movements that allow for left and right interactions through direct feedback, which makes Graz an active BCI paradigm.

C. Multimodal BCI Interfaces

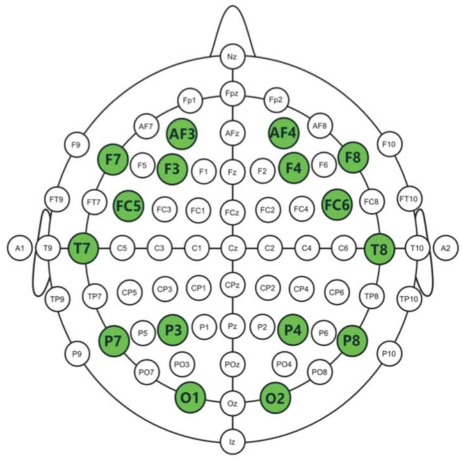
As we have mentioned before, due to the limitations of BCIs [7], researchers have taken an interest in combining BCIs with other more robust modalities [2], [3]. More specifically, for the combination of eye tracking and BCIs, Vilmek and Zander [11] have proposed a spelling system using eye tracking for selection and a BCI for validating the selection. To our knowledge, there have been no attempts to combine these two modalities in the context of games, nor evaluations of different BCI paradigms in this same context. However, there have been studies of such combinations in the medical context, for example, in [17], for the assessment of executive function: Cipresso *et al.* experimented with a combination of eye tracking and P300 and found that the combination of modalities is beneficial and usable, but that the accuracy of the BCI calibration was a crucial element in the performance of the system.

III. Motivations

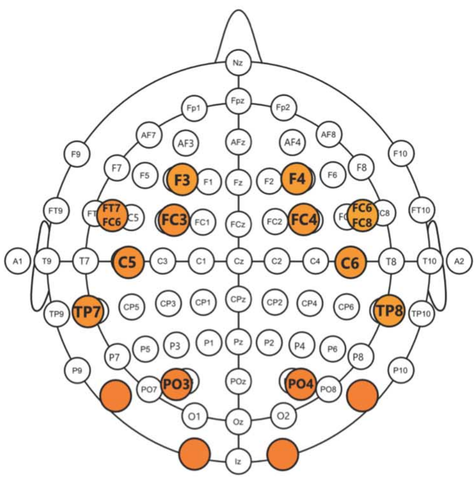
The objective of this paper is to compare the multimodal combination of different BCI paradigms with eye tracking in a gaming context. Targeting this context supposes that we use a BCI compatible with a gaming experience for nondisabled people. This implies three constraints:

— an easy to use solution (no gel and wireless if possible);
— short training time with people who have never used BCI;
— an affordable device.

It is clear that using specialized EEG equipment would lead to much better and reliable results, but it would not fit the usability requirements.



a)



b)

Fig. 1. Ten to twenty electrode placements for Emotiv Epoc. (a) Normal placement. (b) Shifted placement.

Furthermore, experiments carried out by Stytsenko *et al.* [18] suggest that even though the EEG data acquired are less contrasted and precise with the Emotiv Epoc, they are comparable in nature to other conservative devices. Additionally, the mobile electrodes make it easy to shift their positions and to extend the use of Emotiv Epoc to areas of the brain it does not normally cover.

IV. Equipment

For the reasons mentioned above, we have chosen to use the Emotiv Epoc headset for the evaluation of our modality combinations. The Emotiv Epoc [13] is a portable and wireless EEG headset sold by Emotiv Systems. The Epoc has 14 saline electrodes and 14 channels, as well as two reference channels: AF3, AF4, F3, F4, F7, F8, FC5, FC6, P3, P4, P7, P8, T7, T8, O1, and O2 [Fig. 1(a)]. The sampling is sequential at a rate of 128 Hz, with an effective resolution of 14 b. The bandwidth is 0.2–45 Hz and the dynamic input range is 256 mVpp. The main issue raised by the Epoc is the lack of electrodes on the motor cortex: we have tried different strategies to mitigate this issue [see Section V-D and Fig. 1(b)]. As for the eye tracking, we had at our disposal a Tobii T60 eye tracker (Fig. 2), which uses infrared video-oculography (VoG, eye tracking based on filing the motion of the eyes) to track the gaze coordinates. The T60 offers a data rate of 60 Hz, with an accuracy of 0.5°, a drift of 0.1°, a spatial resolution of 0.2°, and a head movement error rate of 0.2°. The head of the subject is allowed to move, with no interruption of the eye tracking, within a window of 44 cm $\times$ 22 cm at a 70-cm distance from the tracker, with a supported distance range between 50 and 80 cm, and a maximum head speed of 20 cm/s. The latency is 33 ms, with a blink recovery time of 17 ms, and a 300-ms recovery time when the tracking is interrupted.

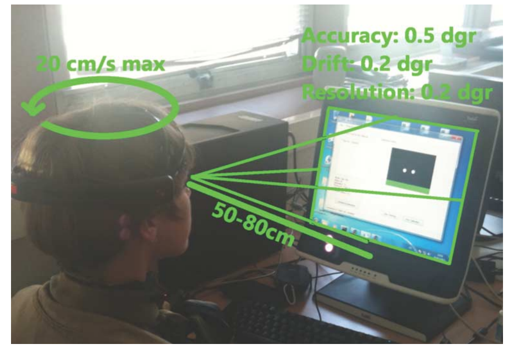


Fig. 2. The Tobii T60 eye tracker.

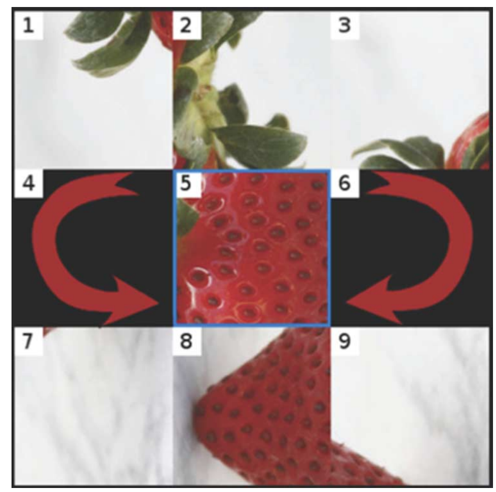


Fig. 3. The game during the rotation phase with SSVEP, in a frame where both arrows are displayed.

V. A Simple Gaming Application

Most of the games rely on very basic interactions, among which the most important are the ability to select an item in the scene (pieces, heroes, objects, etc.) and the ability to trigger actions. For this reason, we have developed a simple puzzle game (Fig. 1) in order to test the different combinations of eye-tracking and BCI modalities. The game involves an image split into tiles in three rows and three columns, where each tile has been rotated once either left or right. The objective of the game is to select the pieces and rotate them all into their correct positions, in order to reconstitute the image.

For the eye-tracking modality, we use a Tobii T60 eye tracker[1] with the software development kit (SDK) provided, and a simple server application that retrieves gaze coordinates and transmits them to the game through a transport control protocol (TCP) socket.

For the BCI aspect, we use the open source BCI programming platform OpenViBE [8], along with the provided BCI scenarios for the Graz protocol and SSVEP, which we have adapted for our application. The OpenViBE designer that runs the scenarios communicates with the application through stimulation events triggered by the scenarios and transmitted to the application through the virtual-reality peripheral network (VRPN) protocol [10]. The game provides four interaction paradigms.

[1]http://www.tobii.com/en/eye-tracking-research/global/products/hardware/tobii-t60t120-eye-tracker/

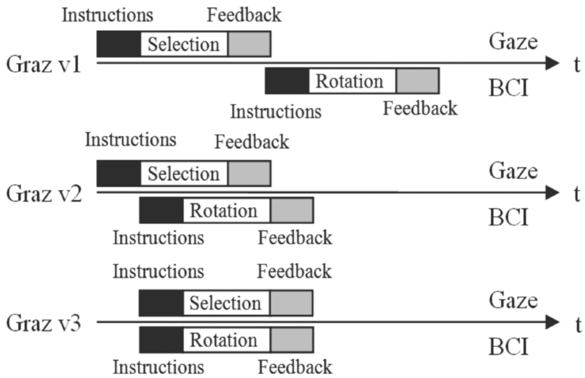


Fig. 4. Three possible combinations of the eye-tracking and Graz modalities.

A. Mouse Version

The mouse version constitutes the "reference" version of the game that only uses mouse input to solve the puzzle. This version is not used for the evaluation directly, but merely helps our test subjects to understand the principle of the game and to gain knowledge about the expected result. As the mouse offers two input modalities (cursor and clicks), the user can move the cursor to select a tile and then, respectively, click left or right to rotate the tile accordingly.

B. Eye Tracker Only

The unimodal eye-tracker version uses eye tracking both for selecting the puzzle tiles and for rotating them. The selection and rotation phases are successive and disjointed. First, the user is instructed to select a tile and is granted 10 s to proceed; it then becomes possible to rotate the tile during 10 s, followed by a 5-s rest period.

For the selection phase, we considered only a dwell-selection approach with a dwell time of 1 s. While click selection is also an interesting approach, we wanted to use only one selection modality for eye tracking and compare it to different BCI approaches, rather than placing ourselves in a more exhaustive setting. The choice for the dwell time was motivated by the fact that we wanted an interaction that was as fast as possible, without, however, introducing unnecessary errors. We reached the compromise of 1 s after performing a series of small tests on ourselves.

As for the rotation phase, arrows appear on either side of the tile to indicate that rotation is possible: to rotate the piece, the user needs to look at the direction in which the tile should be rotated (either on the left or on the right of the tile).

C. Eye Tracker Plus SSVEP

The selection phase remains the same as with the eye-tracker-only version. For the rotation phase, the arrows on either side of the tile flicker at different frequencies (15 and 30 Hz). By looking at the arrow corresponding to the desired rotation direction, evoked visual potentials are generated and then processed by the OpenViBE scenario to trigger the rotation command for the game. Each phase was set to last 10 s.

D. Eye Tracker Plus Graz

Unlike SSVEP, which cannot be used simultaneously with the eye tracker, this becomes possible when using Graz. Thus, the selection and rotation phases do not have to be disjointed, and, consequently, three scenarios arise (Fig. 4):

— the selection phase and the Graz protocol are sequential and disjointed (Graz v1);
— the selection phase starts during the instructions of the Graz protocol (Graz v2);
— the selection phase starts when the left/right feedback from the headset starts being displayed (Graz v3).

In this preliminary experiment, however, we only consider the evaluation of Graz v1, while Graz v2 and Graz v3 will be evaluated in future experiments.

Given the lack of electrodes of Emotiv Epoc over the motor cortex, and the low resulting classification accuracies, for the experiments involving Graz, we placed the Emotiv headset tilted toward the back. Thus, we shifted the electrodes normally on FC5 and FC6 to C5 and C6, the electrodes on F3 and F4 to FC3 and FC4, and the electrodes on AF3 and AF4 to F3 and F4 [Fig. 1(b)].

E. Modality Fusion Engine

In the case of both eye tracking plus SSVEP and eye tracking plus Graz, we use an alternative modality fusion. Following the classification criteria presented in [15], we implemented a procedural notation-less fusion, at a low level for eye tracking (coordinates) and at the dialog level for the BCI modalities (left/right actions).

VI. Experimental Evaluation

A. Objectives of the Evaluation

The objective of the experiments is to evaluate the impact of using a BCI as one of the modalities in a multimodal system. More specifically, we search to identify the extent to which such a modality combination impacts the playability of the game compared to the unimodal eye-tracking version.

B. Experimental Population

We had 30 participants between 22 and 42 years old, among whom there were five women and 25 men. All the participants were complete novices and had never used BCIs beforehand, and were all in good health. The repartition of the individuals in the control groups was random following a uniform distribution.

C. Evaluation Criteria

1) Quantitative Criteria: During a game session, we are primarily interested in knowing how many errors the users make during both the selection and rotation phases. This is why we keep track of the number of correct/incorrect selections as well as the number of correct, incorrect, and total rotations. These values allow us to calculate the error rate for the selection and rotation phases.

Furthermore, we are interested in evaluating the efficiency of the combination of modalities, that is, how long it takes on average to select or rotate a tile. Therefore, at each turn, we keep track of the time it takes to select the correct tile and then to make the correct rotation. Errors will result in higher selection and rotation times.

With fatigue being an important factor in the use of BCI and (to a lesser extent) eye tracking, we undertake several trials for each modality which enables us to track the changes of the error rates and timings, and thus, we are able to evaluate the effect of fatigue on game-play performance.

2) Qualitative Criteria: After each modality, the user was asked general and informal questions about what they liked or did not like; the aspects that they thought hindered or favored the interaction; what was difficult; and so on.

D. Experimental Protocol

Discounting the mouse version, which is only used to explain the principle of the game to the users, there are three different modality combinations to evaluate. Given that each modality generates fatigue, which in turn creates a bias in the performance evaluation of the following modalities, we have established three groups which tested the three modalities in different orders: A) Graz plus SSVEP plus eye tracker; B) SSVEP plus Graz plus eye tracker; and C) eye tracker plus Graz plus SSVEP. Because a training phase is necessary for each of the modalities, it is performed before the modality is used for the first time.

Since we are also interested in observing the effects of fatigue for each modality, the users are asked to solve the game using four different images with different tile rotation distributions: four right and five left, or five right and four left, in different permutations.

VII. Results

During the experiments, we planned to evaluate the three versions of Graz implemented in the game, however, after finishing Graz v1, many subjects failed to fully undergo Graz v2 or Graz v3, or no longer had sufficient motivation given the length of the experiment ($\sim$ 2 h 30 min). Thus, the data collected during the experiments for the two modalities are more than insufficient to make a quantitative analysis, which is why we will merely give our impressions on their performance.

We first present the qualitative and then quantitative feedback from our subjects, followed by a brief analysis.

A. Qualitative Feedback

The users unanimously agreed that selection through gaze was very fast and intuitive; however, eight users (26%) felt that the controls for the rotation operations felt unnatural and uncomfortable.

For Graz, while some users pointed out that it was a very interesting modality, they all complained that the process was slow and tedious and that the classification often seemed random. Some people (60%) found it to be a very natural interaction, while some (73%) found it tedious and tiresome.

Users generally found SSVEP to work better than Graz and to be much easier to use (76%). However, they found the training phase more tedious, and in general people were disturbed or tired quickly due to the flickering. They unanimously expressed the wish for the rotational phase to be shorter.

In general, the users felt that the pure eye-tracking approach was the easiest and least tiring, while admitting that BCI interactions were interesting. Some people suggested that BCIs could be better suited as a complementary and optional modality.

B. Quantitative Feedback

Before analyzing the results we wanted to ensure the statistical significance between the observed groups for each of the metrics we considered. This led us to use a one-way ANOVA for each of the metrics and between all the groups, which is based on the assumptions of independence, normal distribution of the data, and homogeneity of variances.

The first assumption was met, considering that the evaluation of one modality combination did not directly influence the other modalities (assuming that the effects of fatigue were homogeneous between the groups). In order to verify the normality of the distribution, we used normal Q–Q plots and computed the correlation between the theoretical (normal) and empirical quartiles (equivalent to a Shapiro–Wilk test). The correlation values obtained for each of the groups were all above 0.95, which indicates a significant correlation with the normal distribution, by rejecting the null hypothesis that the distributions are not normal $(p \gg 0.05)$. We checked the assumption of the homogeneity of variances using Levene's test of homogeneity of variances, and obtained p-values below 0.05, thus indicating a significant homoscedasticity.

TABLE I
Number of Wrong Selections, Rotations, Selection Time, and Rotation Time (Average and Standard Deviation)

Modality:	Wrong Selections	Wrong Rotations	Avg. Sel. Time(ms)	Avg. Rot. Time(ms)
Pure Eye-tracker	0.930 σ0.524	2.00 σ0.612	1486 σ170.0	668 σ98.9
Eye-tracker + Graz	1.328 σ0.619	3.992 σ0.307	1477 σ147.9	3040 σ301.
Eye-tracker + SSVEP	1.000 σ0.474	1.717 σ0.825	1367 σ117.4	1161 σ261.9
p-value	0.8426	**$1.49\cdot10^{-10}$**	0.0845	**$2.2\cdot10^{-16}$**

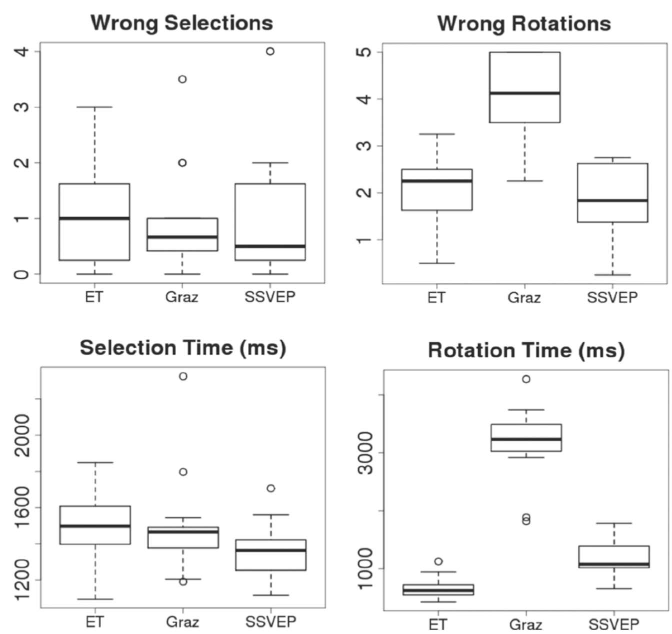


Fig. 5. Wrong rotations and selection, average selection, and rotation times for each modality combination.

Furthermore, whenever we witnessed a significant p-value between the groups for a given metric, we applied the Tukey honestly significant difference (HSD) *post hoc* pairwise test, in order to determine the significance between all possible pairs of groups.

Table I summarizes the number of correct and incorrect selections and rotations, and the average rotation and selection times for each combination of modalities. Since we systematically had significant *post hoc* p-values between the groups when the p-values of ANOVA were significant, we only indicated the ANOVA p-values, which correspond to the maximum *post hoc* p-value across all the group combinations. Furthermore, the distributions of the results are represented graphically in Fig. 5 as box plots.

Before describing the results, it is important to briefly describe the classification accuracies for the BCI modalities after the training phase. On average, for Graz, we had 68.3% for the classification accuracy with a standard deviation of 4.3%. For SSVEP, the average classification accuracy was 79.8% with a standard deviation of 1.3%.

For both the selection errors and times, no variation in the values is significant $(p \gg 0.05)$.

In terms of wrong rotations, the variations are significant $(p<0.05)$: SSVEP is the best, followed by the pure eye tracker (which has a higher variation), while Graz is notably worse with about two more wrong rotations than the two others. This seems to confirm the fact that users found the rotation method with the pure eye tracker unnatural and uncomfortable, whereas the SSVEP approach was more straightforward.

Last, the rotation times, which also exhibit significant variations ($p<0.05$), reflect the comments of the users that rotating with Graz is difficult, leading to notably higher rotation times and rotation time standard deviation of up to 3 s more than the other modalities.

The lowest rotation time was with the eye tracker, which despite more errors, allows for faster rotations. SSVEP is somewhat slower taking on average 1.3 s more per rotation.

As for Graz v2, compared to Graz v1, there seems to be a trend toward higher selection errors, but lower selection times, while rotation errors and times seem to remain similar. For Graz v3, the observation is the same as for the selection tasks, however, higher rotation errors are also observed.

Additionally to studying the results grouped by modality combination, we can make group distinctions based on the order of modalities (control groups), thus we are able to evaluate indirectly whether the order of modalities influences the results and if indeed a specific order causes more fatigue. Among the three groups A, B, and C that we considered in Section VI-D, the only significant result ($p<0.05$) was the selection time for the pure-eye-tracker modality combination where we obtained 1.61 for group A, 0.67 for group B, and 0.86 for group C. Among these three values, Tukey HSD showed that only the difference between A and B was significant ($p<0.05$), thus indicating that when pure eye tracker is evaluated before SSVEP, the selection errors are much greater and that SSVEP generates a lot of fatigue for election tasks with the eyes.

Similarly, when considering the evolution of the results for each modality combination among the successive trials (again for the evaluation of the effects of fatigue), a significant intertrial variation for the number of rotation errors for the eye-tracker-plus-Graz modality combination was shown. Tukey HSD indicated significant variations among all the trial pairs: 3.17 (T1), 3.97 (T2), 3.93 (T3), and 4.10 (T4). These results indicate, at least partly, that there is a clear effect of fatigue for this modality combination.

VIII. Conclusion

Using BCI in a gaming context with nondisabled people is a challenge as it puts a lot of constraints on usability and available technologies. In our work, we attempted to compare several combinations of BCI and eye tracking. From this first experiment, led with 30 participants, we can conclude that, with consumer-grade hardware and novice users, eye tracker plus SSVEP appears to be the most well-rounded and natural combination, as even the pure eye tracker is more error prone while being only slightly faster and more comfortable. In the case of Graz, there are many classifications and practical issues that make its use tiring. However, it appears to be a more intuitive approach in terms of interaction, and is a generally liked interaction principle. Furthermore, experienced users make significantly fewer errors, and we believe that it could be used successfully after improvements to the spatial filters, the classification algorithm, and electrode placement.[2] New experiments with shorter durations on the one hand and more experienced users on the other will either confirm or adjust these results. Furthermore, grouping the results obtained by the control group and by trial highlighted at least some of the significant effects of fatigue. Experiments involving more subjects could potentially indicate further effects of fatigue. Moreover, even breaking up the experiments into several chunks would still leave some room for fatigue between the trials, albeit to a much lesser degree. Additionally, we are currently preparing a similar study and experiments with a g.tec amplifier. However, the results and data will not be available before Spring 2013, thus preventing us from including them in this paper.

[2]The Emotiv Epoc headset has two electrodes on the edges of the motor cortex and no electrodes over it at all.

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