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EEG Single-Trial Classification of Visual, Auditive and Vibratory Feedback Potentials in Brain-Computer Interfaces

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***Abstract*— Feedback stimuli are fundamental components in Brain-Computer Interfaces. It is known that the presentation of feedback stimuli elicits certain brain potentials that can be measured and classified. As stimuli can be given through different sensory modalities, it is important to understand the effects of different types of feedback on brain responses and their impact on classification. This paper presents a protocol used to obtain brain potentials elicited by visual, auditive or vibrotactile feedback stimuli. Experiments were carried out with five different subjects for each modality. Four different single-trial classification strategies were compared, according to the information used to train the classifier, achieving a classification rate of approximately 80% for each modality.**

I. INTRODUCTION

Feedback is a performance information given to a subject as a response of a conduct or task executed. Feedback is known to be a central aspect of learning processes, as it gives the subject a direct association between an accomplished behavior and its desirable or undesirable consequence [1]. Positive and negative feedbacks help to guide the acquisition of new skills and hence are used by therapists to improve the motivation of patients in certain rehabilitation programs [2]. An important aspect of rehabilitation therapies is the type of sensory modalities chosen to provide feedback to the user, which is usually (a combination of) visual, auditive, and tactile feedback [3].

Recently, there has been an increasing interest in the evaluation and monitoring of the user response to feedback. Such information can provide the therapist with indirect parameters of cognitive variables, such as attention, or variables related to the engagement and adherence of a subject to the therapy process [4]. In particular, it is known that feedback stimuli elicit event-related potentials that can be measured with an electroencephalogram (EEG). Furthermore, positive and negative feedbacks produce different brain responses [1], [5]. Negative feedback is related to a family of well-studied potentials known as error potentials, whose online detection has been incorporated in Brain-Computer Interfaces [6]. Based on these results, [7] demonstrated the online classification of feedback potentials evoked by visual feedback.

Despite the visual system being the sensory input that produces the best improvements in learning processes [8], there are many situations where other types of feedback are required, due to the pathology itself or requirements of the rehabilitation process. This is the reason supporting the first attempts to analyze from a psychological point of view different feedback modalities in complex settings, such as driving a wheelchair [3]. This paper analyzes the event-related potentials induced by different modalities of feedback inputs (visual, auditive, and vibrotactile) in a context of performance tasks. This paper also proposes several strategies for single-trial classification of these potentials, with further comparison for the different modalities.

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II. METHODS

A. Experimentation Paradigm and Protocol

The experimental protocol followed in this work is based on the proposal by Miltner in [5]. It consisted of a time-estimation task, where a subject received positive or negative feedback depending on his/her accuracy when trying to delimit a time interval of one second. Each trial started with a visual cue to indicate that the subject had to press a button one second later. Feedback was given 0.6 seconds after the button was pressed. It was positive if the actual elapsed time was closer to 1 second than a threshold α, and negative otherwise. α Represented the accuracy required (the higher α, the lower accuracy required to receive positive feedback).

Three types of feedback modalities were integrated: visual, auditive, and vibrotactile. Visual feedback was given as a green tick (positive) or a red cross (negative). Auditive feedback stimuli were given through two speakers as an harmonious jingle (positive) or a low tone (negative). Vibrotactile feedback was given through five low-power vibrator devices assembled as a customized gadget, and controlled through an Arduino programmable board[1]. The gadget was placed on the left forearm of the subjects, fastened with an elastic band. It vibrated with a low intensity for positive feedback (one vibrator moving at half-power), or with high intensity for negative feedback (five vibrators moving at the same time). Note that vibratory feedback signals were not painful, and the intensities were clearly perceptible and distinguishable by all subjects.

Five different subjects participated in each feedback modality (i.e., totaling 15 subjects). The participants were duly informed about the protocol. For each participant, the experiment was carried out in two sessions, where each session consisted of 30 blocks of 10 trials. The two sessions were performed in different days. In order to balance the

[1] http://www.arduino.cc/

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number of potentials corresponding to positive and negative responses, the threshold α was dynamically computed every ten trials, taking into account all previous results (α decreased as the time-estimation performance of the subject improved, and increased as the performance deteriorated). With this strategy, approximately 150 positive and 150 negative feedback potentials were obtained for each participant and session.

B. Instrumentation

The EEG was recorded using a commercial gTec system, consisting of 32 active EEG electrodes. The electrodes were placed at FP1, FP2, F7, F8, F3, F4, T7, T8, C3, C4, P7, P8, P3, P4, O1, O2, AF3, AF4, FC5, FC6, FC1, FC2, CP5, CP6, CP1, CP2, Fz, FCz, Cz, CPz, Pz and Oz (according to the international 10/10 system). The ground and reference electrodes were placed on FPz and on the left earlobe, respectively. The EEG was digitized at a sampling frequency of 256Hz, power-line notch-filtered to remove the 50Hz line interference, and bandpass-filtered between 0.5 and 10Hz. A Common Average Reference (CAR) filter was applied to remove any background activity detected on the signal. The signal recording and processing, the visual application, and the synchronization between the feedback stimuli and the EEG were developed within the BCI2000 platform [9].

III. Results

This section describes a characterization of the feedback potentials with the different modalities, and the results of the different classification strategies.

A. Characterization of Feedback Potentials

The grand averages were computed for both types of responses (to positive and negative feedbacks) and for all participants, separately for each feedback modality (visual, auditive, and vibratory). The grand averages at FCz channel (commonly used for ERP analysis) are displayed in Figures 1a-c along with the difference between negative and positive responses (referred as difference potentials). Difference potentials evoked by visual and auditive feedbacks are similar in terms of components (the negative components in the auditive case are more pronounced). The difference potential of vibratory feedback shows a significantly different behavior, presenting a notably lower amplitude, and a more oscillating morphology. A deeper analysis of vibratory-evoked responses revealed that the grand averages of each subject presented considerable different typologies. Hence, the total average suffered a great reduction in amplitude. However, the negative component at approximately 500 ms after the stimulus remained similar to the other two modalities.

The brain areas involved in the generation of potentials were studied using source localization (sLoreta [10]). Figures 1d-f display the results. For each feedback modality, the Anterior Cingulate Cortex (ACC, Brodmann Areas 24, 32) was activated at some points in time. The activation was expected, as prior studies showed that erroneous mental processing (measured as the differential activity between negative and positive responses) activates the ACC brain area [1]. In particular, visual and auditive modalities, analyzed on its positive peak (approximately 400 ms after feedback) showed a clear focus of activity on ACC, with best matches being Brodmann Areas 24 and 32 (visual), and 32 and 6 (auditive).

Vibratory modality required extensive analysis. When using sLoreta with the average of all subjects, no focus of activity was found in the areas related to error processing. However, when exploring the individual averages of the participants, ACC was activated for some grand average peaks (see Fig. 1f that shows activation at a negative peak for participant 3). A detailed inspection of the EEG measurements revealed that potentials elicited by vibrotactile feedback had great variations in time latencies, which had an impact on the grand averages. This could be due to the fact that this modality was not obviously associated to what a subject understands as a erroneous/correct stimulus and to differences in reaction time. These dependencies could have an impact on the cognitive process involved in the potentials and thus in the event-related response obtained in the EEG. The users filled out a Likert scale questionnaire to further analyze these effects. The results indicated that the visual feedback group showed a higher satisfaction level than the other groups, being vibrotactile feedback the worst valued. Subjects belonging to the vibrotactile group reported that the two vibration intensities did not evoke directly the associated positive or negative information.

B. Feature Extraction and Classification

An r^2 analysis was carried out to find the spatiotemporal areas with the most significant differences between positive/negative conditions. Figures 1g-i display the average r^2 coefficients for the three feedback modalities. This analysis indicated that the most representative information to differentiate between the two conditions was found in the fronto-central channels (FC1, FC2, CP1, CP2, Fz, FCz, Cz and CPz), at time instants between 200 and 600 milliseconds after feedback presentation. The raw signal for these channels at the time interval selected was downsampled to 64 Hz, and normalized to the range [0-1]. Eight feature vectors (one per selected channel) were concatenated and the total feature vector was composed of 208 features. Note that r^2 coefficients were lower for vibrotactile feedback, suggesting that potentials in this modality were not very discriminative.

Two types of classification results are reported. The first type is an offline classification validated by cross-validation to study the generalization properties. The second type is constituted of four strategies to achieve an online classification more adapted to the online usage of this technique in real settings. The selected classifier was a Support Vector Machine (SVM), as it has been used previously to detect feedback potentials [7], [4]. The SVM was used with a radial basis function kernel and a bandwidth dependent on the number of features.

The offline classification performance is first discussed as a performance benchmark between subjects and modali-

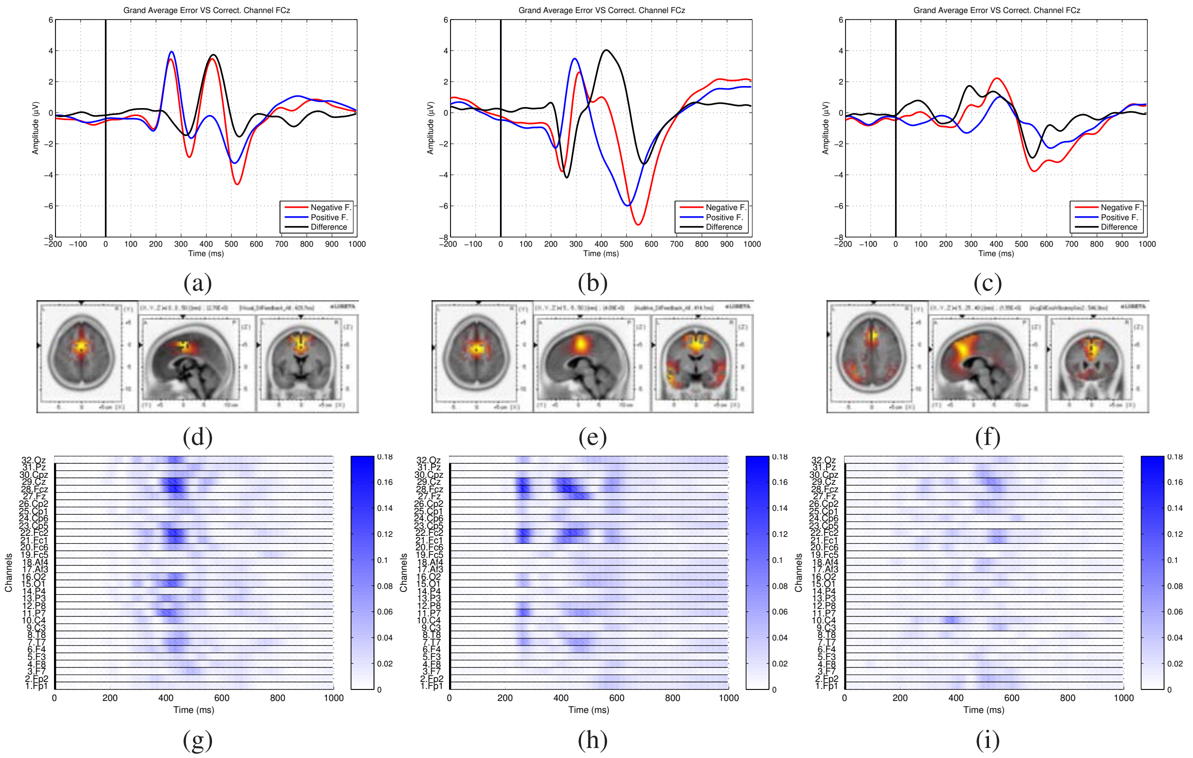

Fig. 1. Analysis carried out for feedback potentials. Left, center and right columns correspond respectively to visual, auditive, and vibrotactile modalities. (a-c) Grand average signals for positive, negative, and difference potentials. The X-axis indicates the time in milliseconds with respect to feedback presentation. (d-f) Source localization main activities found for the average of the subjects in visual and auditive modalities in the main positive peak, and for participant 3 in vibratory modality in its main positive peak. (g-i) r^2 Coefficients averaged for all participants in each modality. Blue areas represent high statistical difference, whereas white areas represent low or no statistical difference.

ties. Results were obtained using a 10-fold cross-validation strategy for each subject, using the datasets from the two sessions together. Results are presented in Table I. The results showed similar accuracies between modalities and subjects. The mean performance for all types of potentials was over 70% in all modalities, and the average accuracies of the three modalities were higher than 75%. Also, all participants achieved similar classification rates, suggesting that the recognition of potentials is stable across participants.

TABLE I

CLASSIFICATION RATES

	Visual			Auditive			Vibratory		
	Pos.F.	Neg.F.	Avg.	Pos.F.	Neg.F.	Avg.	Pos.F.	Neg.F.	Avg.
P.1	72.61	79.97	76.38	89.38	90.40	89.32	70.99	61.97	66.69
P.2	74.21	78.32	76.32	76.70	68.43	73.34	78.80	68.75	73.97
P.3	80.26	83.91	82.01	91.75	81.10	85.95	80.74	73.77	77.02
P.4	87.27	76.06	81.66	88.45	87.10	87.62	86.02	79.41	82.67
P.5	73.75	80.66	76.99	81.33	74.23	78.33	89.54	78.66	84.33
Average	77.62	79.78	**78.67**	85.52	80.25	**82.91**	81.22	72.51	**76.94**

The online single-trial classification of feedback potentials is now analyzed. Four different strategies were evaluated, differing in the data used to train the classifier (i.e. to calibrate the BCI system). In all strategies, the calibration was refined incrementally by retraining the classifier after a certain number of new examples was available. For the results described below, recalibration analysis was done by adding blocks of 10% of the testing dataset (30 trials for the first strategy and 60 for the remaining), and the new retrained classifier was used to classify the following block of the same size.

The first strategy corresponded to a user-specific calibration session (the first experimentation session) and studied the online classification submitted to incremental re-training in the second session. Figure 2a represents the average classification results obtained with this strategy for the three different modalities individually and their average.

Second strategy used a database of participants to train the classifier for each modality. Namely, for each subject, the corresponding classifier was initially calibrated with the other four participants of the same modality. Figure 2b depicts mean classification results of this strategy when executed singly for each modality, and the average between modalities.

The third and fourth strategies used a database of feedback potentials from other subjects and other feedback modalities. The third strategy used only one modality in the calibration process (e.g., training using visual feedback potentials to classify the vibratory potentials), whereas the fourth strategy used two modalities (e.g., visual and auditive feedbacks to classify vibratory). Figure 2c presents the results of training with the five subjects of one modality, and testing with other modality (third strategy). The results are averaged for the five subjects tested individually in each possible combination. Figure 2d shows the results for the three possible train-test settings used by the fourth strategy, in which a classifier was trained with the data of two different modalities, and tested with the subjects of the remaining modality. As in the previous case, the average over the five subjects of the test modality is reported. Recall that the classifiers were incrementally retrained with each subject's own data.

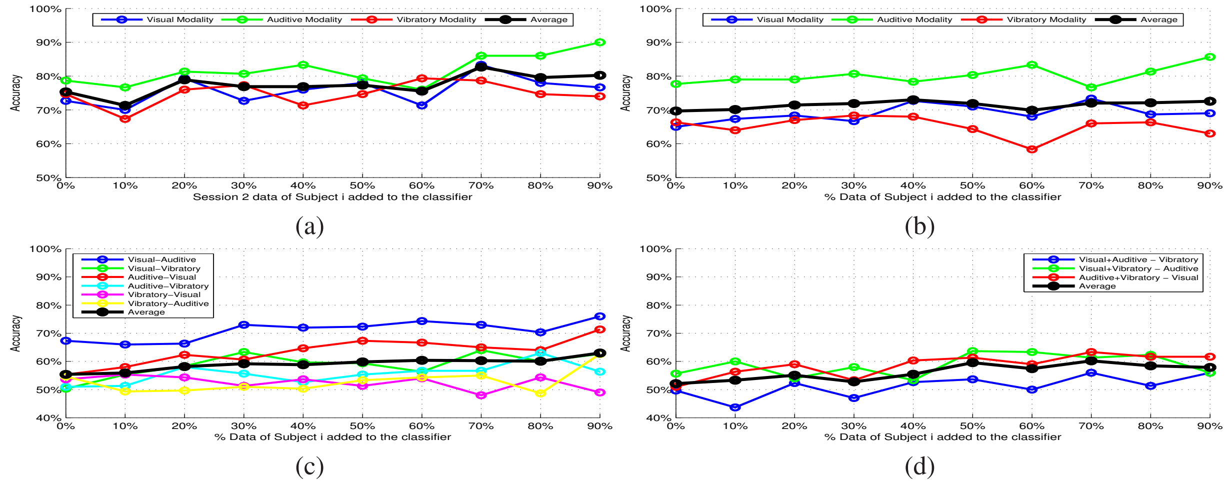

Fig. 2. Results of the incremental classifiers retrained sequentially with data of the studied subject in each case. The X-axis represents the percentage of new examples added to retrain the classifier. The Y-axis indicates the average performance for each classifier configuration. (a) Classifiers built with data of the calibration session of each participant, retrained sequentially with data of the same participant. (b) Classifiers built with data of participants of the same modality, retrained sequentially with data of the studied participant. (c) Classifiers built with data of participants of a different modality, retrained sequentially with data of the studied participant. (d) Classifiers built with data of participants of two different modalities, retrained sequentially with data of the studied participant.

The results provided interesting insights. Firstly, in all cases the classification rate improved as more data from the subject whose potentials were being classified became part of the training set. Secondly, the first strategy gave the best results, as it eventually obtained an average accuracy of 80.22% for the three modalities. For the second strategy, the classification rate started at approximately 70%, without a user-specific calibration, and did not improve much by adding new data (72%).

These two facts indicate that, even within a single modality, the variation of the responses among subjects affects the classifier performance. Also, modalities induce variations in the responses, with auditive feedback achieving the best offline and online classification rates. Finally, the classification rates for strategies that combined different modalities were not as good as the strategies considering only examples of the same modality. This is another clear indication that there are important differences that hinder generalization of classification for the potentials across modalities. However, both classification strategies show an ascending tendency which leaves the door open to improve these results with larger databases, which will better represent the variations of the potentials.

IV. Conclusions and Future Work

This paper addressed the problem of classifying brain potentials evoked after the presentation of feedback in different sensory modalities. The responses obtained using an EEG-based BCI system were analyzed in three different modalities (visual, auditive, and vibratory), with further comparison of four different strategies for online classification of the potentials. The results showed that potentials vary across subjects and modalities. The best classification results were obtained through a user-specific calibration approach, although multiple-user calibration for each modality also provided reasonable performances. The authors are currently investigating the use of these techniques within rehabilitation therapies to provide a measure of the involvement of the subjects. There are also plans of exploring more sophisticated techniques to improve generalization across modalities.

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