Be On the Same Wavelength:
Playing Together with a Brain-Computer Interface Video-Game

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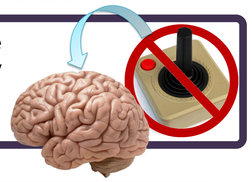
« The joystick is my brain »

Computerized systems controlled by electroencephalography (EEG) cerebral activity have enjoyed a widespread popularity over the past decade [1]. The introduction of Brain-Computer Interface (BCI) technology is particularly interesting for video gaming, in that the cognitive engagement induced by the gameplay may enhance cognitive processing and could help discriminating relevant cerebral activity [2],[3]. We propose a *plug'n'play* collaborative multi-user BCI system, namely Brain Invaders, that outperforms the single-user system using the diversity of the inter-subjects spatio-temporal statistics [4].



Brain Invaders

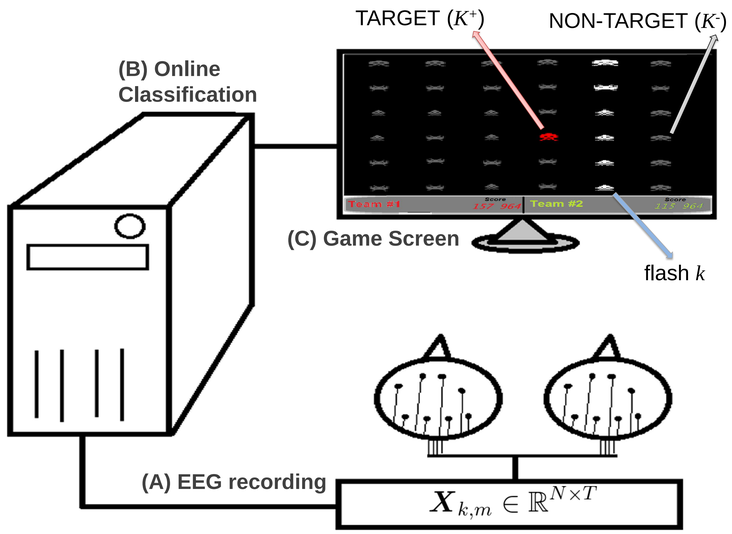


Fig. 1: The EEG signals $X_{k,m}$ of each player m (A) following the kth flash (C) is classified online (B). N is the number of electrodes (16), and T is the length of the trial to classify (1s).

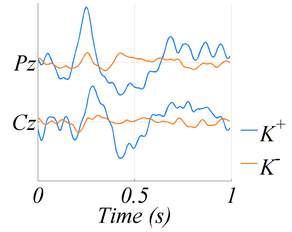


Fig. 2: Ensemble average P_m (1) with $|K^+|$=60 $|K^-|$=300

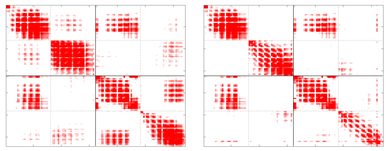


Fig. 3: Extended super covariance matrices (4) for TARGET (left) and NON-TARGET (right).

Collaborative BCI video game

Each level consists of a grid of 6x6 aliens (Fig. 1C), of which one is the TARGET (K^+) and the remaining 35 are NON-TARGET (K^-). The subjects should focus their attention on the target (K^+) while the grid is flashing according to the oddball paradigm [1].

Event-Related Potential (ERP) classification

The classification of the EEG response $X_{k,m}$, namely visual P300 evoked potential (Fig. 2), is exploited to discriminate between the TARGET and the NON-TARGET.

After each repetition of flashes, the game destroys the most probable target according to classification output (6)

Challenges

This is a non-trivial classification tasks as the **Signal-Noise Ratio** (SNR) of the P300 is low and the **variability of shape, amplitude and latency is considerable** across subjects.

Results

Offline classification

To assess the **global performance** in Fig. 5 [4] using the Area Under the ROC Curve (AUC), the MDM (6) is compared to the Step-Wise Linear Discriminant (SWLDA) with the following features:

Classifier	# players	Features
-mean	1	Intra-subject statistics (3)
-multi	2	intra-subject statistics (3)
-hyper	2	intra- and inter-subject statistics (4)

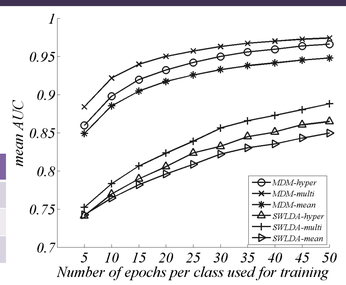


Fig. 5: Classifiers' comparison (34 subjects)

Online classification

17 pairs of participants (22 males, 12 females, *mean age=23.1 +/- 4.2*) played alone (MDM-solo) and together (MDM-hyper) to Brain Invaders. For each repetition the probability to destroy the TARGET is shown in Fig. 6.

Conclusion

For both online and offline studies, the **multi-players classifiers outperform** the solo classifiers. Moreover, we have shown that **this improvement is proportional to the performance homogeneity** within the pair of participants [4].

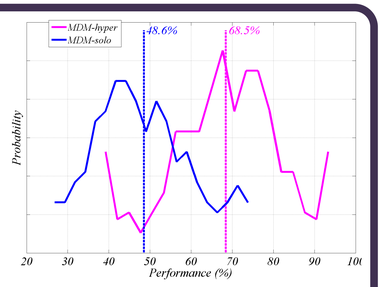


Fig. 6: Distribution of the online performance (34 subjects)

Discussion

- The influence of the inter-subjects statistics for the classification should be assessed.
- The impact of social interactions (e.g. collaboration versus competition) has not been studied with BCI systems.
- A whole new class of classifiers should be designed for detection of coincidental EEG signals in hyperscanning settings (*simultaneous recording during social interaction)*

Online Classification

- Extract each trial $X_{k,m} \in \mathbb{R}^{N \times T}$
- Estimate the **ensemble average** ERP response

$$P_m = \frac{1}{|K^+|} \sum_{k \in K^+} X_{k,m} \quad (1)$$

- Build a "super-trial" by vertical stacking of P_m and X

$$\widetilde{X}_{k,m} = \begin{bmatrix} P_m \\ X_{k,m} \end{bmatrix} \quad (2)$$

- Compute $\widetilde{\Sigma}_{k,m}$ the super **Sample Covariance Matrix** (SCM) of $\widetilde{X}_{k,m}$ embedding the intra-subject's spatio-temporal statistics such as:

$$\widetilde{\Sigma}_{k,m} = \begin{bmatrix} \Sigma_{P_m} & C_{P_m X_{k,m}} \\ C_{X_{k,m} P_m} & \Sigma_{X_{k,m}} \end{bmatrix} \quad (3)$$

- In the case of 2 players, we extend this SCM to include the inter-subject statistics such as (Fig. 3):

$$\widetilde{\Sigma}_k = \begin{bmatrix} \Sigma_{P_1} & C_{P_1 X_{k,1}} & C_{P_1 P_2} & C_{P_1 X_{k,2}} \\ C_{X_{k,1} P_1} & \Sigma_{X_{k,1}} & C_{X_{k,1} P_2} & C_{X_{k,1} X_{k,2}} \\ C_{P_2 P_1} & C_{P_2 X_{k,1}} & \Sigma_{P_2} & C_{P_2 X_{k,2}} \\ C_{X_{k,2} P_1} & C_{X_{k,2} X_{k,1}} & C_{X_{k,2} P_2} & \Sigma_{X_{k,2}} \end{bmatrix} \quad (4)$$

- We classify each super SCM with the **Minimum Distance to Mean covariance matrices classifier (MDM)** using the Riemannian Framework (Fig. 4) in two steps:

a) Using α-divergence function [5], compute the geometric mean covariance matrix $\widetilde{\Sigma}_{K^-}$ and $\widetilde{\Sigma}_{K^+}$, for class K^+ and K^- respectively, **from the previous trials.** This step allows the classifier to be used in an **adaptive way without training session** [6], [7].

b) Compute the **Riemannian distance δ_R** from the kth trial to each class:

$$d_C = \delta_R(\widetilde{\Sigma}_C, \widetilde{\Sigma}_k) \quad , C \in \{K^+, K^-\} \quad (5)$$

- Finally, the estimated class $\hat{y}$ for each trial is:

$$\hat{y} = \underset{C}{argmin}(\delta_R(\widetilde{\Sigma}_C, \widetilde{\Sigma}_k)) \quad , C \in \{K^+, K^-\} \quad (6)$$

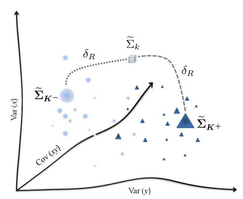


Fig. 4: The Riemannian distance between the current trial $\widetilde{\Sigma}_k$ and the geometric mean Σ_C is the shortest distance (geodesic) in the manifold of Symmetric Positive Definite (SPD) matrices [8].

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