JOURNEES CORTICO 2018

• JJC-ICON'18 •

&

• Meeting Annuel de l'Association CORTICO •

A Toulouse, les 18 & 19 Avril 2018

INTRODUCTION

Nous sommes ravis de vous accueillir pour les Journées CORTICO 2018 à Toulouse ! Nous testons cette année un nouveau format alliant la désormais célèbre « JJC-ICON » (Journée Jeunes Chercheurs en ICO & Neurofeedback) et la Journée Annuelle de l'Association CORTICO. Nous espérons sincèrement que cette formule vous plaira. N'hésitez pas à nous faire vos retours pendant et après la journée. Nous sommes aussi évidemment toujours à la recherche de personnes motivées pour participer aux prochaines éditions ! Avant de vous laisser parcourir tranquillement le magnifique programme qui vous attend pour ces deux jours, nous souhaiterions adresser quelques remerciements : Merci aux intervenants (cours, keynotes, ateliers, discussions thématiques) d'avoir accepté notre invitation et de partager leurs savoirs et leur vision du domaine, Merci aux Jeunes Chercheurs d'avoir soumis leurs travaux et d'avoir préparé de super présentations, Merci aux reviewers d'avoir donné des conseils à ces Jeunes Chercheurs, Merci à l'ISAE de nous avoir prêté ces superbes locaux, Merci aux sponsors de nous avoir aidé à financer cet événement et Merci à vous tous, participants des Journées CORTICO d'être là !

En espérant que ces journées amèneront de belles rencontres scientifiques, de nouvelles perspectives de collaborations, des expériences humaines riches et plus encore !

Bon séjour à Toulouse, et vive le Sud-Ouest boudu !

Camille Jeunet & Raphaëlle Roy - Equipe d'Organisation Expérimentale ;)

// FRANCOIS CABESTAING, PRESIDENT DE CORTICO

Nous sommes en avril 2018 et CORTICO fête déjà son premier anniversaire! Notre COllectif pour la Recherche Transdisciplinaire sur les Interfaces Cerveau-Ordinateur est une association loi 1901 qui a pour but de créer des synergies favorisant l'avancement des recherches, développements et usages relatifs aux interfaces cerveau-ordinateur (ICO). L'un des premiers objectifs concrets de CORTICO consiste à organiser périodiquement des réunions thématiques, comme celle à laquelle vous allez participer aujourd'hui et demain. Ces rencontres offrent l'opportunité à des chercheurs, cliniciens, industriels et étudiants d'échanger et de partager leurs expériences concernant le domaine hautement interdisciplinaire du développement et de l'usage des ICO. N'hésitez pas à visiter notre site (http://www.cortico.fr), devenez membre si vous ne l'êtes pas déjà, et si vous le pouvez aidez-nous à atteindre nos objectifs en consacrant un peu de votre temps à faire connaître notre association!

// JEAN-ARTHUR MICOULAUD-FRANCHI, PRESIDENT DE NEXT

NExT (Neurofeedback Evaluation & Training) est une section de l'Association Française de Psychiatrie Biologique et Neuropsychopharmacologie (AFPBN). L'objectif de la section NeXT est de promouvoir l'évaluation et l'utilisation rigoureuse des techniques de neurofeedback en psychiatrie. NExT structure les enjeux de bonne pratique clinique, de formation et de promotion de la recherche dans le champ du neurofeedback. NExT participe à la rédaction d'articles de synthèse sur le neurofeedback. NExT organise annuellement la journée nationale sur le neurofeedback et des modules de formation sur les enjeux cliniques et pratiques du neurofeedback. Enfin NExT participe à la mise en place d'un réseau de recherche collaborative autour du neurofeedback en psychiatrie avec un lien particulier avec la section STEP (Stimulation Transcrannienne en Psychiatrie) de l'AFPBN afin d'intégrer le neurofeedback dans le champ plus vaste des techniques de neuromodulation en psychiatrie, avec CORTICO afin d'intégrer le neurofeedback dans le champ plus vaste des BCI, et avec la SNCLF (Société de Neurophysiologie Clinique clinique de langue française) dans le cadre des enjeux neurophysiologiques que soulèvent ces techniques.

http://www.afpbn.org/section/next

PROGRAMME

2ème Journée des Jeunes Chercheurs en Interfaces Cerveau-Ordinateur et Neurofeedback

// MERCREDI 18 AVRIL 2018 :

08h30 > Accueil des participants

09h15 > Introduction de la 2ème Journée des Jeunes Chercheurs en ICO & Neurofeedback et de l'Association CORTICO par François Cabestaing

09h30 > Session de cours #1

Session composée de 2 cours de 20 minutes, suivis de 5 minutes d'échanges

Chair : Jérémie Mattout

. **Pr. Stéphane Perrey** (Euromov, Montpellier) : *Influence de la stimulation cérébrale non invasive sur les performances motrices et cognitives chez l'homme.*

. **Pr. Marco Congedo** (Gipsa Lab, Grenoble) : *Introduction au traitement du signal pour les Interfaces Cerveau-Ordinateur (ICO)*

10h30 > Pause

11h00 > Session communications orales des Jeunes Chercheurs

Présentations de 8 minutes + échanges – Abstracts à la fin de ce programme

Chair : Perrine Seguin

. **Pedro L. C. Rodrigues**, Marco Congedo & Christian Jutten, *« Analyse de Procrustes dans la Variété Riemannienne des Matrices Positives Définies : L'apprentissage par Transfert pour les Interfaces Cerveau-Machine »*

. **Nathalie T. H. Gayraud** & Maureen Clerc, *"Optimal Transport Applied to Motor Imagery based BCI"*

. **Hakim Si-Mohammed**, Jimmy Petit, Camille Jeunet, Ferran Argelaguet, Nicolas Roussel, Géry Casiez & Anatole Lécuyer, *"Feasibility, Design and Evaluation of using Brain-Computer Interfaces in Augmented Reality"*

. **Federica Turi**, Nathalie Gayraud & Maureen Clerc, *"Zero-calibration C-VEP BCI using word prediction: a proof of concept"*

. **Louis Korczowski**, Florent Bouchard, Christian Jutten & Marco Congedo, *"Extracting EEG sources of ERP based BCI by Composite Approximate Joint Diagonalization"*

. **Léa Pillette**, Andrzej Cichocki, Bernard N'kaoua & Fabien Lotte, *"Toward distinguishing the different types of attention using EEG signals"*

. **Alban Duprès**, Frédéric Dehais, Sébastien Scannella, Fabien Lotte & Raphaëlle Roy, *« Evaluation de l'attention auditive à partir d'un électroencéphalogramme à 6 électrodes sèches en conditions réelles de vol »*

12h30 > Repas

14h00 > Introduction de NExT par Christophe Daudet

14h15 > Séance « 30'' Teasers »

Introduction des communications affichées des Jeunes Chercheurs

Chair : Camille Jeunet

14h30 > Session de cours #2

Session composée de 2 cours de 20 minutes, suivis de 5 minutes d'échanges

Chair : Sylvain Chevallier

. **Pr. Nadine Vigouroux** (IRIT, Toulouse) : *Apport des BCI pour le domaine de l'Interaction Homme-Machine (IHM) appliquée au Handicap*

. **Pr. Catherine Tessier** (ONERA, Toulouse) : *Pratiques de recherche douteuses*

15h30 > Pause

16h00 > Session communications affichées des Jeunes Chercheurs

Discussions autour de Posters – Abstracts à la fin de ce programme

. **Aurélien Appriou** & Fabien Lotte, *"Analysis and classification of learning-related mental states in EEG signals"*

. **Camille Benaroch**, Camille Jeunet & Fabien Lotte, *"Using computational modelling to better understand and predict Mental-Imagery based BCI (MI-BCI) users' performance"*

. **Florent Bouchard**, Pedro Rodrigues, Jérôme Malick & Marco Congedo, *« Réduction de dimension pour la Séparation Aveugle de Sources »*

. **Sophie Capron**, Léa Lachaud, Takfarinas Medani, Aurore Hakoun & François Vialatte, *"Towards a personalized, flexible cognitive brain computer interface"*

. **Grégoire Cattan** & Marco Congedo, *"Comparison of the EEG signal with and without a passive Head-Mounted Display"*

. **Nicolas Drougard**, Raphaëlle N. Roy & Caroline P. Carvalho Chanel, *"Operator's Mental State Physiological Assessment during Human-Robot Interaction"*

. **Mélodie Fouillen**, Emmanuel Maby, Lucie Le Carrer & Jérémie Mattout, *"Gaze versus EEG-based control of a visual P300 BCI in healthy children"*

. **Giulia Lioi**, Mathis Fleury, Simon Butet, Anatole Lecuyer & Christian Barillot, *"Bimodal EEG-fMRI Neurofeedback for Stroke Rehabilitation"*

. **Jelena Mladenovic**, Jérémy Frey, Emmanuel Christophe, Richard Kronland-Martinet, Jean-Arthur Micoulaud-Franchi & Mitsuko Aramaki, *"Toward congruent BCI feedback"*

. **Sébastien Rimbert**, Nathalie Gayraud, Maureen Clerc, Stéphanie Fleck & Laurent Bougrain, *"Can the MIQ-RS questionnaire be used to estimate the performance of a MI-based BCI?"*

. **Aline Roc**, Léa Pillette & Fabien Lotte, "*Towards understanding the influence of the experimenter on BCI performance"*

17h30 > Clôture de la JJC-ICON'18

> *Réunion du Bureau de l'Association CORTICO*

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19h00 > Repas de Gala à « Les Caves de la Maréchale » [*3 Rue Jules Chalande, Toulouse*]

Meeting Annuel de l'Association CORTICO

(Au cours de cette journée, les interventions se feront en anglais)

// THURSDAY, APRIL 19th 2018:

08h30 > Registration

09h00 > General Opening of the CORTICO Association Annual Meeting by Maureen Clerc

09h15 > <u>Plenary Session: BCI & Society</u>

Duo-Keynote #1 - Ethics for BCIs: the good, the bad and the ugly

Chair : Maureen Clerc

. **Pr. Femke Nijboer** (Leiden University, Netherlands)

. **Pr. Pim Haselager** (Donders Institute, Nijmegen, Netherlands)

10h30 > Coffee Break

11h00 > <u>« Hands-on » workshops</u>

3 super cool workshops will be proposed:

. Ambient tangible objects, by Rémy Ramadour, Jérémy Frey (ULLO start-up)

. fNIRS for brain activity recordings in ecological settings, by Sébastien Scannella (ISAE-SUPAERO)

. Advances in dry EEG electrodes, by Alexander Lechner (g.tec)

12h30 > Lunch Break

14h00 > <u>Plenary Session: La spécialité du Terroir</u>

Duo-Keynote #2 - Socio-affective computing and Neuroergonomics applications

Chair : Raphaëlle Roy

. **Pr. Frédéric Dehais** (ISAE-SUPAERO, Toulouse)

. **Dr. Guillaume Chanel** (Bertin Ergonomie, UX, Facteur Humain & University of Geneva)

15h15 > Coffee Break

15h45 > <u>Thematic Discussions</u>

3 Discussions of 30 minutes each – Abstracts at the end of the program

Chair : François Cabestaing

. BCIs for Human-Computer Interaction, by Hakim Si-Mohammed with Grégoire Cattan, Sylvain Chevalier & Sébastien Rimbert

. The Future of Open-Source BCI Softwares, by Fabien Lotte & Maureen Clerc, with Anton Andreev, Aurélien Appriou & Takfarinas Medani

. Future of CORTICO & Decision regarding the location of the next edition… suspense!, by François Cabestaing, Camille Jeunet & Raphaëlle Roy

17h30 > Closing of the CORTICO Association Annual Meeting & Warm Goodbyes!

PLAN D'ACCES DE LA CONFERENCE

// LIEU DE LA CONFERENCE : ISAE-SUPAERO

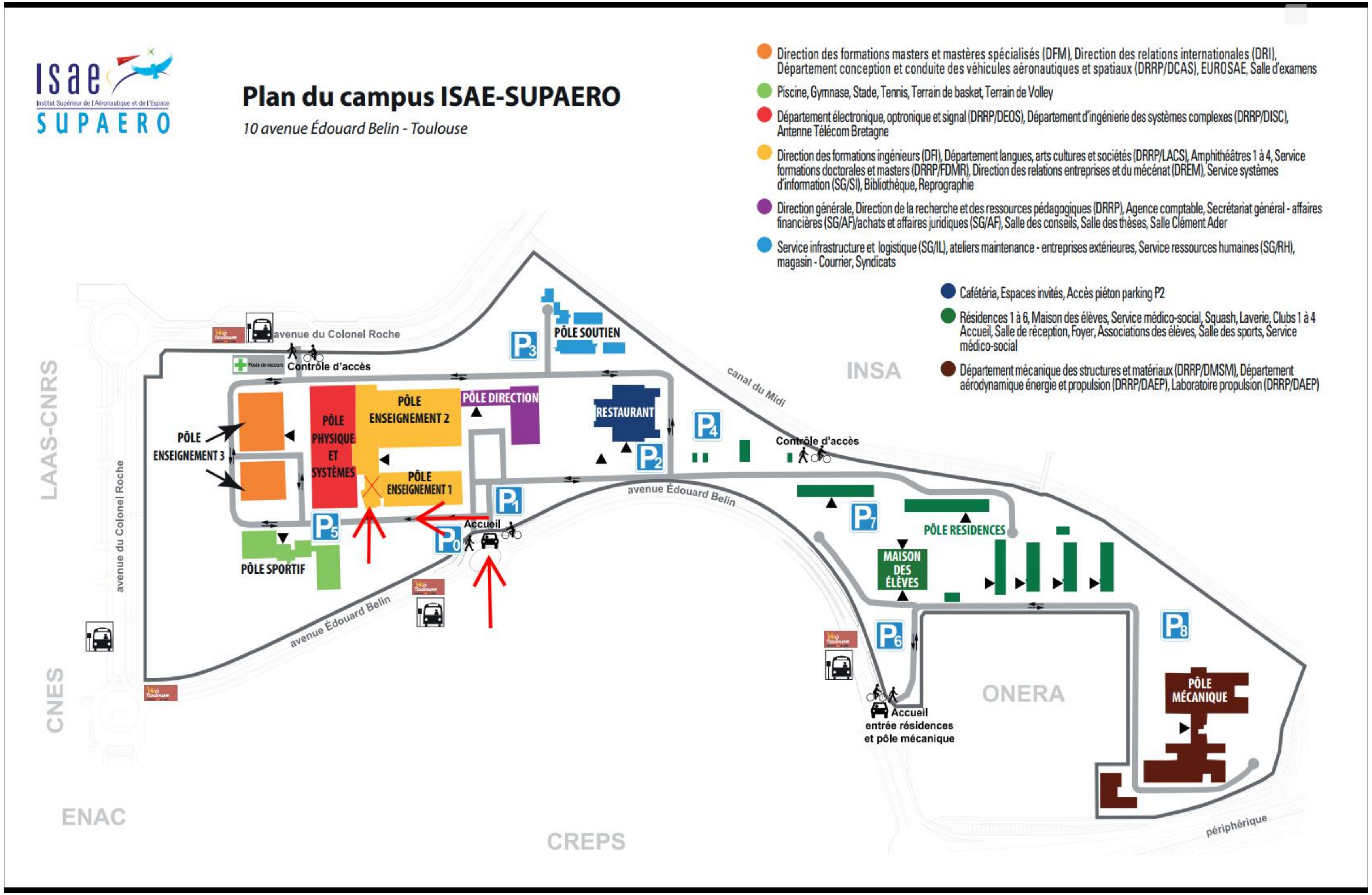
Adresse : 10 avenue Edouard Belin – TOULOUSE – Pôle d'Enseignement 1 (voir le plan ci-dessous)
Coordonnées GPS : Latitude N 43° 34' 00'' - Longitude E 1° 28' 29''

Accès :

- **Depuis l'aéroport de Toulouse-Blagnac :** Prendre la navette jusqu'au centre-ville. S'arrêter près de la gare SNCF.
- **En bus depuis la gare SNCF :** A l'arrêt de bus (Tisséo) situé en face de la gare (boulevard Pierre Semard), prendre le bus (Tisséo) 27 direction « Ramonville-Saint-Agne » jusqu'à l'arrêt « ISAE CAMPUS SUPAERO ».
- **En métro depuis la gare SNCF :**
  - *Le moins de marche à pied :* Quand vous êtes à la gare, un couloir souterrain vous mène à la station de métro « MARENGO-SNCF ». Prendre la ligne A du métro direction « Basso Cambo » jusqu'à la station « JEAN-JAURES », puis prendre la ligne B du métro direction « Ramonville » jusqu'au terminus "RAMONVILLE". Prendre ensuite le bus (Tisséo) 27 direction Lycée Toulouse-Lautrec jusqu'à l'arrêt « ISAE CAMPUS SUPAERO ».
  - *Le plus rapide :* Quand vous êtes à la gare, un couloir souterrain vous mène à la station de métro « MARENGO-SNCF ». Prendre la ligne A du métro direction « Basso Cambo » jusqu'à la station « JEAN-JAURES », puis prendre la ligne B direction Ramonville jusqu'à l'arrêt "Faculté de Pharmacie". Prendre ensuite le bus (Tisséo) n°78 direction « Lycée de St Orens » jusqu'à l'arrêt « ENAC » puis remonter l'Avenue Édouard Belin jusqu'au Campus ISAE-SUPAERO (5 min à pied).
  - *Le moins de correspondance :* Quand vous êtes à la gare, un couloir souterrain vous mène à la station de métro « MARENGO-SNCF ». Prendre la ligne A du métro direction « BALMA-GRAMONT » jusqu'à la station « JOLIMONT », puis prendre le bus (Tisséo) n°37 direction « RAMONVILLE » jusqu'à l'arrêt « ENAC » et remonter l'Avenue Édouard Belin jusqu'au Campus ISAE-SUPAERO (5 min à pied).
- **Depuis le centre-ville par autobus :** Au métro Jolimont (ligne A) prendre le bus (Tisséo) n°37 direction « RAMONVILLE » jusqu'à l'arrêt « ENAC » puis remonter l'Avenue Édouard Belin jusqu'au Campus ISAE-SUPAERO (5 min à pied).
- **Par le périphérique :** Prendre le périphérique extérieur (direction Montpellier), puis suivre la direction "Toulouse- centre / Foix / Tarbes" (panneau vert). Sortir à la Sortie 20, suivre « Complexe scientifique de Rangueil ».
- **En taxi :** Demander le "Complexe scientifique de RANGUEIL" puis l'ISAE - Campus SUPAERO (en face du CREPS).

Salles :

- Hall & Forum : accueil, sponsors, posters, pauses-café/thé/jus
- Amphi 4 : séances plénières
- Salles de cours à l'étage, 61 116, 61 118, 61 119 : ateliers


Plan du campus ISAE-SUPAERO
10 avenue Édouard Belin - Toulouse
Direction des formations masters et mastères spécialisés (DFM), Direction des relations internationales (DRI), Département conception et conduite des véhicules aéronautiques et spatiaux (DRRP/DCAS), EUROSAE, Salle d'examens
Piscine, Gymnase, Stade, Tennis, Terrain de basket, Terrain de Volley
Département électronique, optronique et signal (DRRP/DEOS), Département d'ingénierie des systèmes complexes (DRRP/DISC), Antenne Télécom Bretagne
Direction des formations ingénieurs (DFI), Département langues, arts cultures et sociétés (DRRP/LACS), Amphithéâtres 1 à 4, Service formations doctorales et masters (DRRP/FDMR), Direction des relations entreprises et du mécénat (DREM), Service systèmes d'information (SG/SI), Bibliothèque, Reprographie
Direction générale, Direction de la recherche et des ressources pédagogiques (DRRP), Agence comptable, Secrétariat général - affaires financières (SG/AF)/achats et affaires juridiques (SG/AF), Salle des conseils, Salle des thèses, Salle Clément Ader
Service infrastructure et logistique (SG/IL), ateliers maintenance - entreprises extérieures, Service ressources humaines (SG/RH), magasin - Courrier, Syndicats
Cafétéria, Espaces invités, Accès piéton parking P2
Résidences 1 à 6, Maison des élèves, Service médico-social, Squash, Laverie, Clubs 1 à 4 Accueil, Salle de réception, Foyer, Associations des élèves, Salle des sports, Service médico-social
Département mécanique des structures et matériaux (DRRP/DMSM), Département aérodynamique énergie et propulsion (DRRP/DAEP), Laboratoire propulsion (DRRP/DAEP)
avenue du Colonel Roche
Contrôle d'accès
PÔLE SOUTIEN
PÔLE ENSEIGNEMENT 3
PÔLE PHYSIQUE ET SYSTÈMES
PÔLE ENSEIGNEMENT 2
PÔLE ENSEIGNEMENT 1
PÔLE DIRECTION
RESTAURANT
PÔLE SPORTIF
Accueil
avenue Édouard Belin
canal du Midi
INSA
Contrôle d'accès
PÔLE RESIDENCES
MAISON DES ÉLÈVES
Accueil entrée résidences et pôle mécanique
ONERA
PÔLE MÉCANIQUE
périphérique
LAAS-CNRS
CNES
ENAC
CREPS
P0
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P8

ABSTRACTS DES JEUNES CHERCHEURS

Les abstracts sont présentés ci-dessous par ordre alphabétique.

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BRAIN INVADERS, A BCI VIDEO GAME USING RECENT ADVANCEMENTS IN RIEMANNIAN GEOMETRY

Anton Andreev, Marco Congedo, Alexandre Barachant, Louis Korczowski

Gipsa Lab, Grenoble, France

We will present the Brain Invaders (Congedo et al., 2011), a fully functional BCI game and the GIPSA-lab extensions (GEO), a free plug-in for the OpenViBE platform allowing to set up advanced Brain-Computer Interfaces (BCI) based on the oddball paradigm using the P300 event-related potentials. The GEO component contains the implementation of several algorithms we have developed at GIPSA-lab over the past 10 years. Brain Invaders can be executed in: train/online, adaptive and multiplayer mode (Korczowski, Barachant, Andreev, Jutten, & Congedo, 2016). All three are implemented using Riemannian geometry (Andreev, Barachant, Lotte, & Congedo, 2016), (Congedo, Barachant, & Bhatia, 2017) and in particular the Minimum Distance to Mean (MDM) classifier. The novelty here is a "Plug and Play" (Barachant & Congedo, 2014) system, that is, a system that is smartly initialized and adapted to the user. Also the training of a session can be used for a different session. All this allows the user to play without calibration, with the algorithm adapting to the user in the first minute of the game.

Brain Invaders and GEO are free to download. We provide a Windows installer. They are both licensed under GPL v3.0. The algorithms, architecture and communication between Brain Invaders and GEO can be reused in other BCI applications.

Home page: https://bitbucket.org/toncho11/openvibe-gipsa-extensions

Download page: https://bitbucket.org/toncho11/openvibe-gipsa-extensions/downloads

Andreev, A., Barachant, A., Lotte, F., & Congedo, M. (2016). Recreational Applications of OpenViBE: Brain Invaders and Use-the-Force. In M. Clerc, L. Bougrain, & F. Lotte (Eds.), Brain-Computer Interfaces 2: Technology and Applications (Vol. chap. 14, pp. 241–257). John Wiley.

Barachant, A., & Congedo, M. (2014). A Plug&Play P300 BCI Using Information Geometry. arXiv:1409.0107 [Cs, Stat].

Congedo, M., Barachant, A., & Bhatia, R. (2017). Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review. Brain-Computer Interfaces, 4(3), 155–174.

Congedo, M., Goyat, M., Tarrin, N., Ionescu, G., Varnet, L., Rivet, B., … Jutten, C. (2011). "Brain Invaders": a prototype of an open-source P300- based video game working with the OpenViBE platform. In 5th International Brain-Computer Interface Conference 2011 (BCI 2011) (pp. 280–283). Graz, Austria.

Korczowski, L., Barachant, A., Andreev, A., Jutten, C., & Congedo, M. (2016). "Brain Invaders 2" : an open source Plug & Play multi-user BCI videogame. In 6th International Brain-Computer Interface Meeting (p. 224). Pacific Grove, CA, United States: BCI Society.

#

ANALYSIS AND CLASSIFICATION OF LEARNING-RELATED MENTAL STATES IN EEG SIGNALS

Aurélien Appriou [1,2], Fabien Lotte [1,2]

1 Potioc, Inria Bordeaux Sud-Ouest, France - 2 LaBRI, Univ. Bordeaux, CNRS, INP), France

Although promising, BCIs are still barely used outside laboratories due to their poor robustness. Moreover, they are sensitive to noise, outliers and the non-stationarity of electroencephalographic (EEG) signals.

These lacks of robustness and reliability are notably due to inefficiencies in different steps of the BCI process, going along data acquisition, signal processing, classification and human training. We propose an approach, aiming at improving the human training in BCI protocols by improving the classification of workload variations. Indeed, a better understanding of human learning-related mental states such as workload could lead to a personalized training for each subject, possibly improving BCI reliability altogether. The data set used for this study comes from [1], and was designed to perform realistic workload classification. Two levels of cognitive workload are evoked using two distinct N-back tasks. We aimed at classifying these two cognitive workload levels by comparing four classification algorithms, using BCPy. BCPy is an open-source python platform for offline EEG decoding, proposing different machine learning algorithms for EEG signals classification. We applied promising modern machine learning algorithms to analyze the workload : Riemannian Geometry and a shallow Convolutional Neural Network (CNN). We then compare them to the state-of-the-art methods, including a Common Spatial Pattern (CSP) filter coupled with a Linear Discriminant Analysis (LDA) classifier; and a Filter Bank CSP (FBCSP) filter coupled with a LDA classifier. This study has been made with both user-specific and user-independent calibrations, to go towards calibration-free systems. Our results showed that a shallow CNN obtained the best performance (user-specific : mean = 72.7% ± 9.1; user-independent : mean = 63.7% ± 7.7) in both conditions, being significantly better than the CSP coupled with a LDA (user-specific : mean accuracy = 67% ± 8.1; user-independant : mean = 58.0% ± 6.7) which is a reference for EEG signals classification.

[1] C Mühl, C Jeunet, and F Lotte (2014). EEG-based workload estimation across affective contexts. Frontiers in Neuroscience 8 (2014), 1–15.

#

USING COMPUTATIONAL MODELLING TO BETTER UNDERSTAND AND PREDICT MENTAL-IMAGERY BASED BCI (MI-BCI) USERS' PERFORMANCE

Camille Benaroch [1], Camille Jeunet [2,3], Fabien Lotte [1,4]

1 Potioc, Inria Bordeaux Sud-Ouest, France - 2 CNBI, EPFL, Switzerland – 3 Hybrid, Inria Rennes Bretagne-Atlantique - 4 LaBRI, Univ. Bordeaux, CNRS, INP), France

Mental-Imagery based Brain-Computer Interfaces (MI-BCIs) use signals produced during mental imagery tasks to control the system. Using an MI-BCI requires a dedicated user-training. The more users practice, the better they should become. In other words, their mental commands will most likely be more often correctly recognized by the system. Current MI-BCIs are rather unreliable, which is due at least in part to the use of inappropriate user-training procedures. Understanding the processes underlying user-training by modelling it computationally could enable us to improve MI-BCI training protocols and adapt the latter to the profile of each user. Our objective is to create a statistical/probabilistic model of training that could explain, if not predict, the learning rate and the performances of a BCI user over training time using user's personality, skills, state and timing of the experiment. In order to build such a model, we are currently using data obtained from three different studies [1, 2, 3], which are based on the same protocol. In total, 42 participants were instructed to learn to control an MI-BCI by performing three MI-tasks (i.e., left-hand motor imagery, mental rotation and mental subtraction) across different training sessions (3 to 6 depending on the experiment). Data are divided into four categories: the user's traits (e.g., mental rotation, tension), the user's state (e.g., level of fatigue and difficulty), the timing of the experiment (e.g., hour, lapse between two sessions) and the user performances (e.g., online classification accuracy -CA-, offline cross validation CA). Preliminary analyses revealed positive correlations between MI-BCI performances and mental rotation scores among two of the three studies, suggesting that spatial abilities play a major role in MI-BCI users' abilities to learn to perform MI tasks, which is consistent with the literature [4].

1. Jeunet, C., N'Kaoua, B., Subramanian, S., Hachet, M., & Lotte, F. (2015). *Predicting mental imagery-based BCI performance from personality, cognitive profile and neurophysiological patterns. PloS one, 10(12), e0143962.*
2. Pillette, L., Jeunet, C., Mansencal, B., N'Kambou, R., N'Kaoua, B., & Lotte, F. (2017, September). *PEANUT: Personalised Emotional Agent for Neurotechnology User-Training. In 7th International BCI Conference.*
3. Teillet, S., Lotte, F., N'Kaoua, B., & Jeunet, C. (2016, October). *Towards a spatial ability training to improve Mental Imagery based Brain-Computer Interface (MI-BCI) performance: A Pilot study. In Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on (pp. 003664-003669). IEEE.*
4. Jeunet, C. (2016). *Understanding & Improving Mental-Imagery Based Brain-Computer Interface (Mi-Bci) User-Training: towards A New Generation Of Reliable, Efficient & Accessible Brain-Computer Interfaces (Doctoral dissertation, Université de Bordeaux).*

#

RÉDUCTION DE DIMENSION POUR LA SÉPARATION AVEUGLE DE SOURCES

Florent Bouchard, Pedro Rodrigues, Jérôme Malick, Marco Congedo

Gipsa Lab, Grenoble, France

Les interfaces cerveau-machine (BCI) et le neurofeedback basés sur l'électroencéphalographie (EEG) s'appuient sur l'identification et l'analyse de certains marqueurs de l'activité cérébrale comme les potentiels évoqués ou certains types d'ondes continues comme par exemple les ondes alpha ou beta.Le problème principal de l'EEG est que les activités des différentes sources cérébrales sont mélangées au niveau des signaux enregistrés par les électrodes. Il semble donc très intéressant d'être en mesure d'effectuer un démélange, ce qui peut être accompli par la séparation de sources. De plus, il y a généralement moins de sources que de capteurs qui ont une contribution significative dans les enregistrements, donc 'utilisation de techniques de réduction de dimension est bien souvent nécessaire.Dans cette communication, nous considérons le problème de la réduction de dimension dans le cadre de la séparation aveugle de sources. Nous proposons (1) un nouveau modèle basé sur la diagonalisation par blocs conjointe qui permet simultanément de réduire la dimension et de retrouver les sources et (2), une approche par optimisation Riemannienne pour le résoudre, originale dans ce contexte. Notre modèle produit des sources indépendantes du bruit et moins sensibles à l'estimation à priori du nombre de sources. L'efficacité de notre modèle par rapport à l'état de l'art est illustré sur la séparation de sources d'un enregistrement EEG.

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COMPARISON OF THE EEG SIGNAL WITH AND WITHOUT A PASSIVE HEAD-MOUNTED DISPLAY

Grégoire Cattan [1], Marco Congedo [1]

1 Gipsa Lab, Grenoble, France

In the domain of Virtual Reality (VR), a Passive Head-Mounted Display (PHMD) is a mask constituted of binocular lens and a support in which we insert a smartphone (Figure 1). The term passive refers to the fact they do not inboard other electronic components such as a gyroscope. A PHMD is a suitable candidate to couple VR with Brain-Computer Interface (BCI) technology since PHMDs are affordable and provide a built-in structure for the electroencephalographic (EEG) cap. However, the impact of such material on the EEG signal has never been studied. In this work, we recruited 12 subjects and evaluated the spectral characteristics of the continuously recorded EEG signal with and without the use of a PHMD. Two smartphones S6 (Samsung, Seoul, South Korea) were used for this experiment, one being switched-on and the other switched-off. We asked the subjects to sit while we regularly switched between the two conditions. For each subject, we recorded five blocks with the smartphone switched-on and five blocks with the smartphone switched-off. Each block consisted in one minute of data recording with the eye opened. The sequence of the 10 blocks were randomized before the experiment to allow the use of an exact randomization test for testing hypotheses (Edgington & Onghena, 2007). We then compared the amplitude spectrum of the signal for frequencies between 0.5 and 36Hz. To test the null hypothesis that the spectra do not differ in the two experimental conditions we performed two-tailed univariate randomization tests (Edgington & Onghena, 2007),t-max multiple-comparison randomization tests (Nichols & Holmes, 2002) and cluster-based randomization tests (Maris & Oostenveld, 2007). The results (Figure 2, Figure 3) show that the PHMD do not impact the EEG signal, suggesting that the use of BCI with a PHMD-based Virtual Reality is possible.

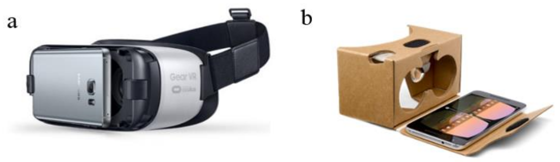

Figure 1. SamsungGear (a) can be used in passive (inserting a smartphone) or active (with on-board electronic supplied) mode. The Google Cardboard (b) is a very simple passive HMD.

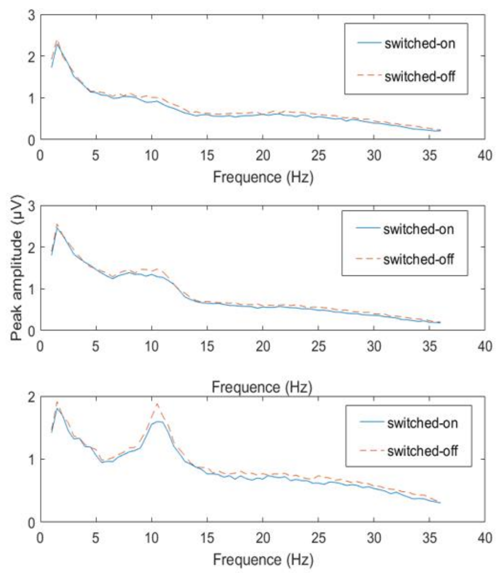

Figure 3. Amplitude spectrum of the Fp1 (up), CZ (center) and Oz (bottom) electrodes in the two experimental conditions.

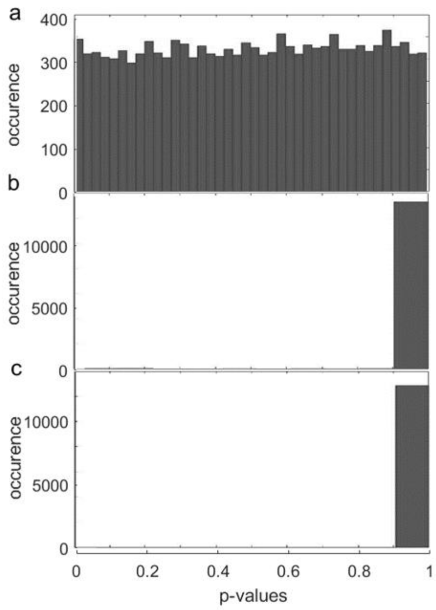

Figure 2. Histogram of p-values for the randomization tests (a, non-corrected), t-max test (b, corrected), cluster-based test (c, corrected).

Edgington, E., & Onghena, P. (2007). Randomization Tests, Fourth Edition. CRC Press.

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. Journal of Neuroscience Methods, 164(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Nichols, T. E., & Holmes, A. P. (2002). Nonparametric permutation tests for functional neuroimaging: a primer with examples. Human Brain Mapping, 15(1), 1–25.

mples. Human Brain Mapping, 15(1), 1–25.

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TOWARDS A PERSONALIZED, FLEXIBLE COGNITIVE BRAIN COMPUTER INTERFACE

Sophie Capron, Léa Lachaud, Takfarinas Medani, Aurore Hakoun, François Vialatte

ESPCI, Paris, France

Our long term goal is to create a brain computer interface measuring cognitive load in real time, and then to develop a cognitive neurofeedback protocol for healthy adults using electroencephalography. In this first study, we attempted to build various classification models each aiming at discriminating between two cognitive states (e. g. high versus low cognitive load, mindful state versus non mindful…). 30 healthy adult subjects performed a one hour long series of cognitive tasks while their electroencephalographic activity was recorded. In order to reduce the risk of identifying task specific markers (Gerjets et al, 2014), 10 different tasks were used. Each task type was presented in at least two versions, visual and auditory, in order to account for modality specific behavior. After each task, subjects were presented with an extract of the NASA Task Load Index (Hart et al, 1988) to collect their perceived workload and success. After artifact removal was performed on the recordings, feature extraction and ranking were performed using the SIGMA toolbox developed by the Brain Plasticity Laboratory's BCI team (Medani et al, 2017). For each cognitive state of interest, the 5 best features were selected. For each subject, half of the recorded data was used with these features to train support vector machine models that were then validated on the remaining half of the data. The average accuracy of these models ranges from 0.75 to 0.85. In order to account for individual differences, the participants were also presented with a socio-demographic questionnaire, as well as personality questionnaires. Despite the small sample size, this allows us to refine our interpretation of the subjects' perceived states and identify attention points for our next studies.

Gerjets, P., Walter, C., Rosenstiel, W., Bogdan, M., & Zander, T. O. (2014). Cognitive State Monitoring and the Design of Adaptive Instruction in Digital Environments: Lessons Learned from Cognitive Workload Assessment using a Passive Brain-Computer Interface Approach. Frontiers in Neuroscience, 8:385.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In Human Mental Workload (Vol. 52, pp. 239-250). Amsterdam (North Holland Press): Hancock, Peter A.; Meshkati, Najmedin.

Medani, T., Mora-Sánchez, A., Jaumard-Hakoun, A., Dreyfus, G., & Vialatte, F. (2017). Sigmabox: towards a simple and efficient Matlab toolbox for EEG signal processing and classification. Neuroadaptive Technologies 2017. Berlin.

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ANALYSE DE PROCRUSTES DANS LA VARIÉTÉ RIEMANNIENNE DES MATRICES POSITIVES DÉFINIES – L'APPRENTRISSAGE PAR TRANSFER POUR LES INTERFACES CERVEAU-MACHINE

Pedro L. Coelho Rodrigues, Marco Congedo, Christian Jutten

Gipsa Lab, Grenoble, France

Une étape essentielle lors de l'usage d'une interface cerveau-machine (BCI) est la calibration, où le système s'adapte aux particularités de l'utilisateur et ajuste ses paramètres afin de classifier au mieux les signaux enregistrés. La nécessité de calibration vient du fait que les statistiques des signaux d'une session peuvent être très différentes de celles d'une autre session ou venant d'un autre sujet. Par conséquent, un classifieur optimisé pour un certain jeu de données de BCI n'est pas forcément réutilisable. Cette problématique est au coeur de ce qu'on appelle l'apprentissage par transfert. Dans cette communication, nous présentons une méthode qui permet de manipuler les données de deux sujets (ou sessions) et faire correspondre leurs statistiques au mieux. Pour cela, nous utilisons une approche basée sur l'Analyse de Procrustes, où les données sont transformées avec des opérations géométriques simples comme la translation, dilatation et rotation. En particulier, nous considérons que les points à manipuler sont des matrices positives définies (e.g. matrices de covariance spatiale des signaux) et les opérations considérées respectent donc la géométrie intrinsèque de la variété Riemannienne à laquelle elles appartiennent. Nous appelons cette méthode l'Analyse de Procrustes Riemannienne (RPA). Nous avons investigué l'apport de la RPA dans des situations où le classifieur est optimisé pour un sujet mais utilisé pour la classification de signaux d'un sujet différent. Les résultats obtenus sur quatre bases de données BCI diferentes (dont trois paradigmes distincts) montrent une supériorité moyenne statistiquement significative de la classification suivi de la RPA par rapport au cas où les données ne sont pas transformées. Nous avons aussi observé de meilleures performances avec la RPA en relation à la calibration avec peu de données, démontrant que la RPA peut être une bonne stratégie pour initialiser les systèmes BCI à partir de données pré-enregistrées.

MI-Physionet	MEAN ACCURACY		
N	direct	recent.	RPA
1	0.52	0.55	0.55
5	0.53	0.59	0.61
10	0.54	0.61	0.63
15	0.55	0.63	0.64

MI-GigaDB	MEAN ACCURACY		
N	direct	recent.	RPA
1	0.55	0.58	0.55
5	0.55	0.60	0.61
10	0.56	0.62	0.64
25	0.58	0.65	0.67

SSVEP	MEAN ACCURACY		
N	direct	recent.	RPA
1	0.59	0.59	0.61
2	0.64	0.65	0.68
4	0.71	0.72	0.76
6	0.75	0.77	0.80

P300	MEAN AUC		
N	direct	recent.	RPA
6	0.49	0.59	0.55
12	0.50	0.57	0.57
32	0.52	0.54	0.57
48	0.53	0.54	0.56

Figure 1: Valeurs moyennes de la classification inter-subject pour trois méthodes diferentes : "direct", sans aucune transformation, "recent.", moyennes géométriques égalisées, et "RPA", quand on utilise l'Analyse de Procrustes Riemannienne. Les résultats sont pour quatre bases de données diferentes. Le paramètre N correspond au nombre d'exemples disponibles dans le sous-ensemble d'entraînement du sujet "target".

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OPERATOR'S MENTAL STATE PHYSIOLOGICAL ASSESSMENT DURING HUMAN-ROBOT INTERACTION

Nicolas Drougard[1], Raphaëlle N. Roy[1], Guillaume Chanel[2]

1 Univ. Fédérale de Toulouse, ISAE-SUPAERO, Toulouse, France - 2 Bertin Ergonomie, UX , Facteur Humain & Univ. Geneva, Switzerland

To our knowledge, research is still scarce on the use of physiological measures to perform an online assessment of operators during human-robot interaction. In order to progress towards systems that would dynamically adapt to operators' mental states, a first step is to determine an adequate protocol that elicits variations in engagement. Hence, this work presents an analysis of physiological data streams coming from human operators performing a human-robot mission. The considered mission puts into practice the cooperation between a firefighter robot and a human operator to extinguish fires. The robot can be autonomous or manually operated. In addition to dealing with the robot direction, the operator has to perform another difficult task which consists in managing the water level in a refill tank. The duration of fixations per area of interest (AOI) and the length of inter-beat intervals were extracted from eye-tracking and ECG data collected on 17 participants. From the ECG, Heart Rate Variability (HRV) and instant Heart Rate Variability (IHRV) were computed. Main results are lower HRV and IHRV during the mission than during the rest session, which highlights that the mission did indeed engage the participants. Impact of the robot operation mode could also be observed. In autonomous mode, the tank task engaged more the participants than in manual mode. Moreover, the number and durations of fixations on AOIs corresponding to the two main tasks were negatively correlated. Markers on these AOIs were correlated with the mode of the robot. Also, the IHRV marker was correlated with the mode, the tank's AOI and with the remaining time for mission's end. These data confirm the elicitation of various engagement states during HRI. The next step is to perform classification of these states in an online fashion, as well as to add other physiological measures such as cerebral ones.

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EVALUATION DE L'ATTENTION AUDITIVE À PARTIR D'UN ÉLECTROENCÉPHALOGRAMME À 6 ÉLECTRODES SÈCHES EN CONDITIONS RÉELLES DE VOL

Alban Duprès[1], Frédéric Dehais[1], Sébastien Scannella[1], Fabien Lotte[2], Raphaëlle N. Roy[1]

1 Univ. Fédérale de Toulouse, ISAE-SUPAERO, Toulouse, France - 2 Inria Bordeaux Sud Ouest, LaBRI (Univ Bordeaux / Bordeaux INP / CNRS), Potioc Team, Talence, France

Introduction : Le pilotage nécessite un engagement important de la part du pilote, engendrant dans certaines situations critiques des accidents liés à une surdité inattentionnelle (SI) aux alarmes (Dehais et al., 2013). L'objectif de notre étude est d'évaluer l'anticipation de ces erreurs, en analysant l'électroencéphalogramme (EEG) du pilote. En effet, la SI est caractérisée par des marqueurs neurophysiologiques spécifiques, susceptibles d'être détectés automatiquement par une interface cerveau-ordinateur passive (ICOp). Parmi ces marqueurs, nous privilégions les potentiels liés à l'évènement (ERPs) dans la mesure où ils se caractérisent par une diminution de l'amplitude de leurs composantes N100 et P300 lors d'une SI (Giraudet et al., 2015). Une première étape vers l'élaboration d'une ICOp est d'évaluer l'apparition et la détection de tels ERPs dans des signaux EEG enregistrés en vol.

Matériel et Méthode : Afin de générer ces ERPs, l'expérimentation comprend une tâche de « odd-ball » (Lotte et al., 2009), durant laquelle le pilote compte les sons déviants (25% des sons). Environ 220 stimuli ont été présentés toutes les 2 à 5 secondes à 7 pilotes. L'activité EEG a été enregistrée grâce à 6 électrodes sèches (ENOBIO, Neuroelectrics) en position Fz, Cz, Pz, Oz, P3, et P4.

Résultats et discussion : On observe une P300 significativement ($p<0.05$) plus ample lors des sons déviants, sur les électrodes Fz, Pz, et P3. Pour discriminer les sons déviants et standards nous avons évalué les performances (taux de bonne classification) d'un LDA (Linear Discriminant Analysis) classique (moyenne=0,49, écart-type=0,04) et d'un LDA dit « shrinkage » (Blankertz et al., 2010 ; moyenne=0,55, écart-type=0,04), grâce à une procédure de validation croisée utilisant un nombre équilibré d'essais par classe. Les résultats statistiques au niveau du groupe sont encourageants, sachant que l'EEG a été enregistré dans un environnement fortement bruité. Néanmoins, les performances de classification sont encore insuffisantes pour espérer développer une ICOp fiable. Le principal défi réside dans le débruitage des signaux afin d'améliorer les performances de classification.

Dehais, F., Causse, M., Vachon, F., Régis, N., Menant, E. and Tremblay, S. (2014). Failure to Detect Critical Auditory Alerts in the Cockpit: Evidence for Inattentional Deafness. Human Factors: The Journal of the Human Factors and Ergonomics Society, 56(4), pp.631-644.

Giraudet, L., St-Louis, M., Scannella, S. and Causse, M. (2015). P300 Event-Related Potential as an Indicator of Inattentional Deafness?. PLOS ONE, 10(2).

Lotte, F., Fujisawa, J., Touyama, H., Ito, R., Michitaka, H. and Lécuyer, A. (2009). Towards Ambulatory Brain-Computer Interfaces: A Pilot Study with P300 Signals. In Proceedings of the International Conference on Advances in Computer Enterntainment Technology (pp. 336- 339).

Blankertz, B., Lemm, S., Treder, M., Haufe, S. and Müller, K. (2010). Single-trial analysis and classification of ERP components — A tutorial. NeuroImage, 56(2), pp.814-825

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GAZE VERSUS EEG-BASED CONTROL OF A VISUAL P300 BCI IN HEALTHY CHILDREN

M. Fouillen[1,2], E. Maby[1,2], L. Le Carrer[1,2,3], J. Mattout[1,2]

1 Brain Dynamics and Cognition Team, Lyon Neuroscience Research Center, INSERM U1028-CNRS, UMR5292, Lyon, France- 2 University Lyon 1, Lyon, France - 3 Hospices Civils de Lyon, Lyon, France

P300 based interfaces are known to require overt attention, i.e. gaze orientation towards the targets, to reach high enough performance (Brunner et al., 2010). However, as attention and gaze direction are partly dissociated, what remains elusive is the contribution of attention to P300 BCI performance, independently of eye gaze. To tackle this question, 32 healthy children were given the task to play the game connect-four (Maby, Perrin, Bertrand, Sanchez, & Mattout, 2012). Importantly, during one block, participants controlled the game through EEG signals, while during the other block the control was based on remote eye-tracking (ET). Half of the children started playing based on EEG (Group 1), while the other half started based on ET (Group 2). Children were told and believed throughout the task that control was only and always based on

EEG. The true target was given by the ET output. Offline, we computed the BCI accuracy for each Group and each condition. A 2x2 repeated measure ANOVA (Time * Control mode) revealed a trend for the interaction ($p = 0.064$). This is driven by a drop of performance in the second block of Group 1 subjects as shown on Figure 1. A likely explanation is that, at the beginning, all children did their best to follow the instruction and carefully pay attention to the target. However, over time, this effort became more difficult to produce and vanished in the group whose feedback/performance was not relying on this effort anymore. Indeed, participants in Group 2 who needed to maintain such an effort, did so. Conversely, participants in Group 1 who could simply rely on eye gaze to perform well in the second block, did alleviate their attentional effort, yielding a drop in BCI Accuracy.

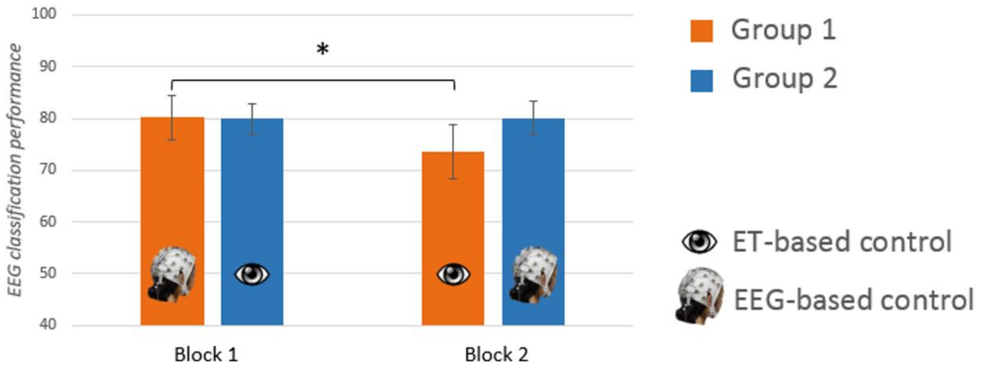

Figure 1. *Averaged BCI Accuracy for each group and each block, showing the drop of performance of participants in Group 1 during the second block. Error bars indicate S.E.M.*

Brunner, P., Joshi, S., Briskin, S., Wolpaw, J. R., Bischof, H., & Schalk, G. (2010). Does the “P300” speller depend on eye gaze? Journal of Neural Engineering, 7(5), 056013. https://doi.org/10.1088/1741-2560/7/5/056013

Maby, E., Perrin, M., Bertrand, O., Sanchez, G., & Mattout, J. (2012). BCI Could Make Old Two-Player Games Even More Fun: A Proof of Concept with “Connect Four.” Advances in Human-Computer Interaction, 2012, 8. https://doi.org/10.1155/2012/124728

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OPTIMAL TRANSPORT APPLIED TO MOTOR IMAGERY BASED BCI

Nathalie Gayraud, Maureen Clerc

Université Côte d'Azur, Inria Sophia-Antipolis-Méditerranée, France

The design of zero-calibration Brain Computer Interfaces (BCI) is a critical research topic. Several transfer learning approaches have been proposed to confront this issue [1]. In particular, for multiclass Motor Imagery-based BCI, the BCI seeks to extract discriminative features from the recorded EEG signal. In subject-to-subject transfer learning strategies, these features are learned from existing labeled sessions recorded with a different subject than the one using the BCI. Nevertheless, due to a phenomenon known as covariate shift [2], the domain of new features can be different from the domain of the ones learned during training. Thus, the resulting classifier may fail to generalize well across subjects. We solve this issue by using discrete regularized Optimal Transport (OT) with class labels [3,4]. OT theory studies the problem of transporting probability mass between distributions with respect to a cost function. The method learns a transformation which is assumed to have caused the shift between the two domains and applies its inverse to transport new features onto the domain of the existing ones. We perform offline experiments using Database 2a of BCI competition IV. Considering all possible pairings of subjects where one subject is used to train the BCI and another to test it, we apply OT along with two transfer learning methods. The first consists of learning multiclass CSP features [5], and using them to train an LDA classifier. The second is a Riemannian Geometry-based classifier [6], as they have been effective in countering the subject-to-subject variability [1]. Since the classification task is to separate 4 imagined movements, we use Cohen's kappa value as a performance measure. Our results, displayed in Figure 1, show that OT improves the average results of both techniques. These results demonstrate that OT is a powerful pre-processing tool that can enhance the result of transfer-learning approaches.

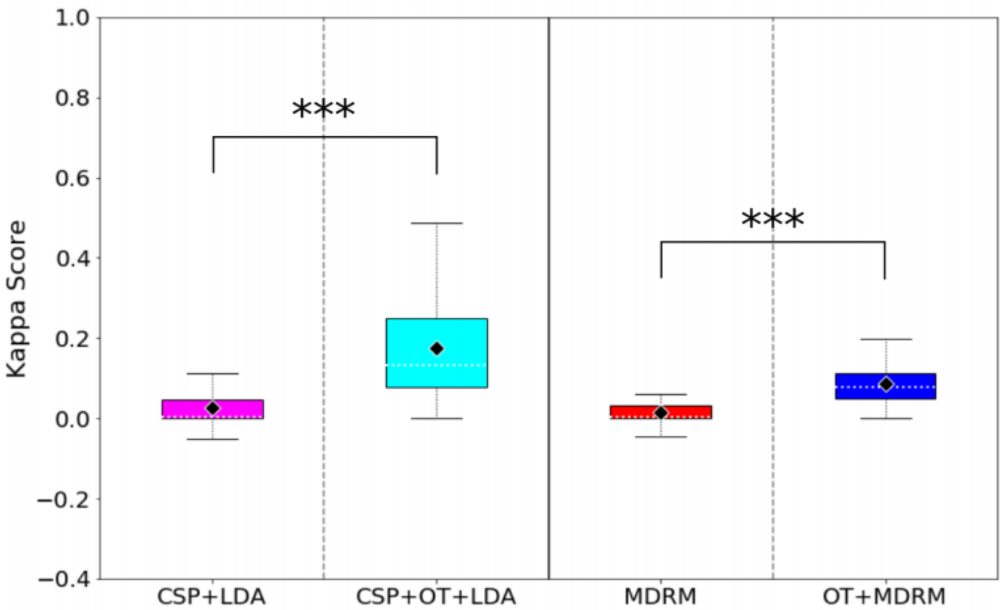

Figure 1. Results from subject-to-subject transfer learning offline experiments. Each box shows the result of 72 pairwise experiments. On the left, the first two boxes reflect the performance of a Linear Discriminant Analysis (LDA) classifier, trained with features extracted from 10 multiclass Common Spatial Patterns (CSP) filters [5], without and with OT. Transporting the feature vectors of the test set significantly improves the generalization capacity of the classifier. On the right, a similar experiment, where OT is applied before the Minimum Distance to Riemannian Mean classification algorithm [6]. Once more, the results are greatly improved after the application of our OT method.

[1] Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., & Yger, F. (2018). A Review of Classification Algorithms for EEG-based Brain-Computer Interfaces: A 10-year Update. Journal of neural engineering.

[2] Clerc, M., Bougrain, L., & Lotte, F. (Eds.). (2016). Adaptive Methods in Machine Learning. In Brain-Computer Interfaces 1: Methods and Perspectives. John Wiley & Sons.

[3] Courty, N., Flamary, R., Tuia, D., & Rakotomamonjy, A. (2017). Optimal transport for domain adaptation. IEEE transactions on pattern analysis and machine intelligence, 39(9), 1853-1865.

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EXTRACTING EEG SOURCES OF ERP BASED BCI BY COMPOSITE APPROXIMATE JOINT DIAGONALIZATION

Louis Korczowski, Florent Bouchard, Christian Jutten, Marco Congedo

Gipsa Lab, Grenoble, France

Context: Event Related Potentials (ERP) are commonly used for Brain Computer Interface (BCI) because of their stereotypical response to an induced sensory stimuli (e.g. visual, haptic, auditory, etc.). Among the challenge of those BCI are the low signal-noise ratio and the short transient state of the ERP. A common strategy to deal with those data is to exploit both spatial and temporal diversity such as Riemannian geometry using extended covariance matrices (Barachant, Bonnet, Congedo, & Jutten, 2013) or spatio-temporal filtering (Yu et al., 2011). We are interested to exploit this statistical diversity in order to extract physiologically plausible sources that can use for classification but also for automatic noise source removal (EOG, EMG, etc.) in an unsupervised way. Blind Source Separation (BSS) deals with those issues by extracting EEG sources (Delorme, Palmer, Onton, Oostenveld, & Makeig, 2012) but it is known to be challenging for ERP.

Proposed Solution: In order to extract physiologically accurate EEG sources including ERPs, we proposed a composite EEG model to extract simultaneously ongoing EEG sources and evoked sources that have a linear and a bilinear structure respectively. To do so, we used Approximate Joint Diagonalization (AJD) of cospectra, covariances and temporal estimation to find both spatial and temporal unmixing matrices.

Results: Our method, Composite Approximate Joint Diagonalization (CAJD) was compared to the standard AJD and also to the bilinear variant (BAJD). We have shown that CAJD shows better convergence (in simulation) and it is able to separate the different ERP components (N100, P200, P300, etc.) better than AJD and BAJD (in real BCI data). The source localization is more robust for CAJD and we show that it can be used to remove automatically non-EEG sources. Among the other advantages, the ERP sources stereotypical time-series are captured within the temporal unmixing matrix. Those evidence show that CAJD can be a potent tool for ERP-based BCI.

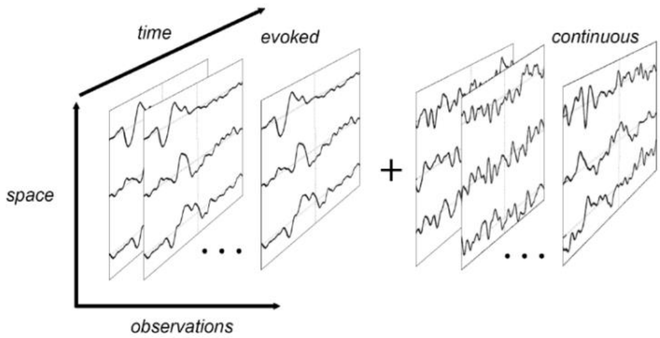

Figure 1 CAJD aims to extract simultaneously the a linear contribution (ongoing EEG) and bilinear contribution (evoked EEG) of data.

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Delorme, A., Palmer, J., Onton, J., Oostenveld, R., & Makeig, S. (2012). Independent EEG Sources Are Dipolar. PLOS ONE, 7(2), e30135. https://doi.org/10.1371/journal.pone.0030135

Yu, K., Shen, K., Shao, S., Ng, W. C., Kwok, K., & Li, X. (2011). Common spatio-temporal pattern for single-trial detection of event-related potential in rapid serial visual presentation triage. IEEE Transactions on Bio-Medical Engineering, 58(9), 2513–2520. https://doi.org/10.1109/TBME.2011.2158542

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BIMODAL EEG-FMRI NEUROFEEDBACK FOR STROKE REHABILITATION

Giulia Lioi, Mathis Fleury, Simon Butet, Anatole Lécuyer, Christian Barillot

Inria Rennes Bretagne-Atlantique

Neurofeedback (NF)[1] has potential to be applied for stroke rehabilitation [2], [3], however its effectiveness has not been thoroughly assessed yet. NF approaches are usually based on real-time monitoring of brain activity using a single imaging technique. Recent studies [4]–[6] have revealed the potential of combining EEG and fMRI to achieve a more efficient and specific self-regulation, which may be critical in clinical applications. We tested the feasibility of applying bimodal EEG-MRI NF for stroke rehabilitation in two chronic patients affected by left hemiplegia. The protocol included a calibration step (motor imagery of hemiplegic hand) and two NF sessions (5 minutes each). In this preliminary study, we did not perform longer training sessions to reduce patients' fatigue and movements' artifacts. The experiment was run using a NF platform [7] that performs real-time EEG-fMRI processing and NF presentation. The NF was computed as the average (normalized by the activity during rest) of BOLD and EEG activity in regions of interest (ROI) identified over the ipsilesional motor cortex. The fMRI ROIs and optimal EEG filter were identified during calibration. The NF metaphor consisted of a ball moving on a gauge and was updated with a frequency of 1 Hz for the fMRI component and 4 Hz for the EEG. Both patients were able to self-regulate their brain activity during the NF sessions: they increased both ROI BOLD activity and EEG event-related desynchronization during the NF blocks as compared to resting; however, the EEG component was harder to modulate than the BOLD activity and the performances differed between sessions. The correlation of the BOLD signal with the task varied depending on the ROI targeted and was particularly high for the supplementary motor area. The patients were highly motivated to engage and satisfied with the NF animation, as assessed with a qualitative questionnaire.

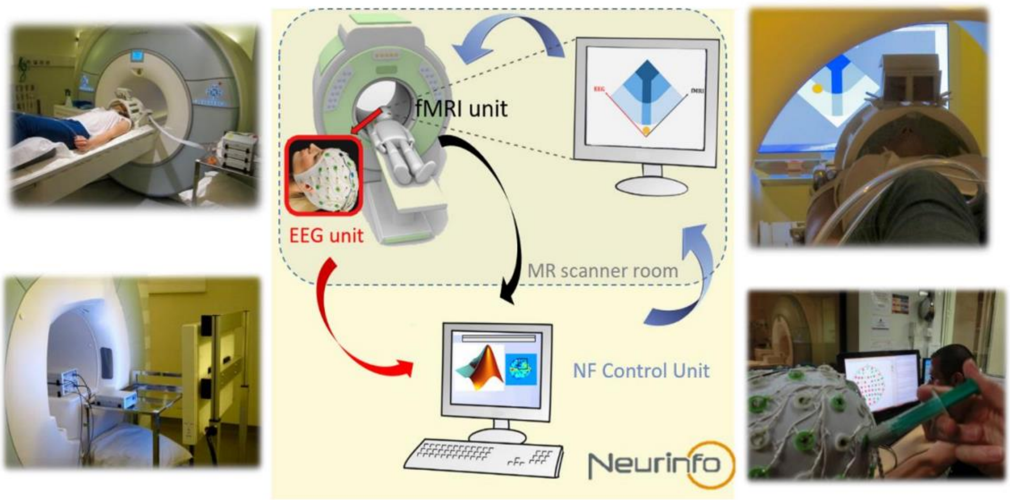

Figure 1. Schematic of the Bimodal EEG-fMRI platform (Neurinfo, CHU Pontchaillou, Rennes)

[1] D. C. Hammond, "What is Neurofeedback: An Update," J. Neurother., vol. 15, no. 4, pp. 305– 336, 2011.

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[3] F. Pichiorri et al., "Brain-computer interface boosts motor imagery practice during stroke recovery," Ann. Neurol., vol. 77, no. 5, pp. 851–865, 2015.

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#

TOWARD CONGRUENT BCI FEEDBACK

Jelena Mladenovic [1,2], Emmanuel Christophe[3], Richard Kronland-Martinet[3], Jean-Arthur Micoulaud-Franchi [4], Mitsuko Aramaki [3]

1 Potioc, Inria Bordeaux Sud-Ouest, France - 2 INSERM, Lyon, France - 3 Prism, CNRS, Marseille, France - 4 SANPSY, CNRS, Bordeaux, France

We explored possibilities to increase motor imagery (MI) BCI performance by implementing Flow theory. According to this theory, by adapting the task difficulty to one's skills and making engaging content, one can reach a state of flow, i.e., to be fully immersed in a task, forgetting about the self and the environment, and thus reaching higher performance rates (1). In this experiment, to evoke the state of flow, music was played in the background, the BCI task was playful (a video game), and the difficulty was adapted in real-time according to user performance (classifier output). Subjects reported to have been perturbed by the rhythm of the music which did not follow their imagined movement. This inspired us to explore the benefits of a task-related (congruent) and synchronised audio feedback which would comply with the user's imagined movements. Congruent visual environment in MI BCI has been researched in virtual reality, giving a sense of body ownership illusion, and showed to be more robust and improve performance (3). On the other hand, the effects of a congruent audio environment, have not yet been explicitly explored in BCI. We investigate the potential of an audio congruent task, tackling the sensori illusion of presence by providing realistic audio feedback using a synthesizer from (4). We present preliminary results to show the benefits of a congruent, audio MI feedback of feet as opposed to no congruent feedback using abstract sound. We found a significant difference ($p < 0.05$) in classification accuracy when a binary classifier was trained offline separately on the "congruent" and "non-congruent" runs (respectively 66.1%, SD: 7.45 and 63.9% SD: 7.8, 10-fold cross-validation) (5). This study encourages further research on congruent BCI tasks, which can both induce flow and assist users to achieve more stable MI.

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TOWARD DISTINGUISHING THE DIFFERENT TYPES OF ATTENTION USING EEG SIGNALS

Léa Pillette [1,2], Andrezej Cichockin[3,4], Bernard N'Kaoua[5], Fabien Lotte [1,2]

1 Potioc, Inria Bordeaux Sud-Ouest, France - 2 LaBRI, Univ. Bordeaux, CNRS, INP), France - 3 Riken BSI, Wakoshi, Japan - 4 Skoltech, Moscow, Russia - 5 Handicap, Activity, Cognition, Health, Univ. Bordeaux, France

"Attention" is a generic word encompassing alertness and sustained attentions, referring to the intensity of attention (i.e., strength), as well as selective and divided attentions, referring to its selectivity (i.e., amount of monitored information) [10]. BCI literature indicates an influence of both users' attention traits and states (i.e., respectively stable and unstable attentional characteristics) on the ability to control a BCI. Though the types of attention involved remain unclear [1,3,4,5]. Therefore, assessing which types of attention are involved during BCI use might provide information to improve BCI usability. Before testing this hypothesis, we first needed to assess if the different types of attention are recognizable using EEG. Hence, we asked 16 participants to perform different tasks, each assessing one type of attention presented above, while we recorded their EEG. For each task, participants had to react as fast as possible -by pressing a keyboard spacebar- to the appearance of target stimuli. The tasks and types of attention were differentiated by the type of sensorial modality of the stimuli, number of distractors, presence of warnings before the stimuli and length of the task, in accordance with the literature [2,7,8,9]. Results from the preliminary analysis tend to indicate that EEG patterns of the different types of attention are distinguishable from both one another, and the resting state's (i.e., when participants are asked to relax and not to perform any specific task). For example, by using a Common Spatial Pattern filtering in the alpha range (8-12Hz) and a Linear Discriminant Analysis classifier, with 5-fold cross-validation we found that sustained attention is recognizable from the resting state with a classification accuracy of [55%, 92.5%] (above chance levels [62.5%, 65%] for 15 participants [6]). An inter-subject analysis of the differences of activation between these states suggested a key role of the frontal cortex (see figure).

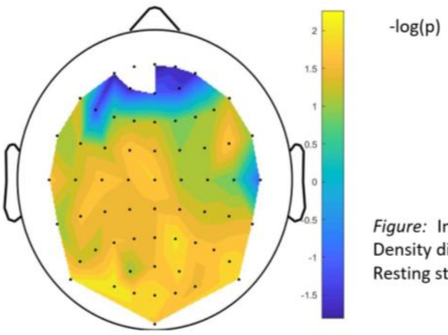

Figure: Inter-subject mean significance in Power Spectral Density differences in alpha range for Sustained attention vs. Resting state (obtained using a t-test).

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CAN THE MIQ-RS QUESTIONNAIRE BE USED TO ESTIMATE THE PERFORMANCE OF A MI-BASED BCI?

Sébastien Rimbert[1,2], Nathalie Gayraud[3], Maureen Clerc[3], Stéphanie Fleck[4], Laurent Bougrain[2,1]

1 Inria Nancy Grand-Est, France - 2 Univ. Lorraine, LORIA, UMR 7503, Vandoeuvre-lès-Nancy, France - 3 Inria Sophia Antipolis-Méditerranée and Université Côte d'Azur, France - 4 Univ. Lorraine- PErSEUs EA 7312, Île du Saulcy Metz, France

Introduction: Predicting a subject's ability to use the interface with good accuracy is one of the major issues in the motor Brain-Computer interface (BCI) domain. A few recent studies show that subjective questionnaires could be used to predict the performance of motor imagery (MI) based BCI. Indeed, the Kinesthetic and Visual Imagery Questionnaire (KVIQ), could allow a better predictability of BCI-illiterate cases [1]. Another more recent questionnaire called the Motor Imagery Questionnaire Revised-Second Edition (MIQ-RS) is a suitable option for examining MI ability [2]. In 2016, Marchesotti et al. found that the representation of subjective behaviour, calculated using the MIQ-RS questionnaire, and the control of the BCI were intimately linked [3]. However, in these studies [1, 3], the performance of the classifier was calculated for a right-hand MI versus a left-hand MI task. In this study, we classify between resting state and imagined movement, which is a relevant classification task in BCI research [4]. The aim of this study is to answer the following question for a resting state versus MI classification task: can the MIQ-RS be used to estimate the performance of an MI-based BCI?

Material, Methods and Results: 36 right-handed healthy subjects (12 females; aged 31.3 years ± 14.4) were tested for their perception level of their visual and kinesthetic MI ability via the MIQ-RS questionnaire. EEG signals were recorded with a Biosemi Active Two 32-channel EEG system during a MI task (i.e. a single closing of the right hand) in one session of 40 trials. The EEG signal was bandpassed using a Butterworth filter between 8 and 30 Hz and segmented into 3.5 second trials. A Riemannian-based Tangent Space classification method [5] coupled with a Logistic Regression classifier was used to generate classification results in a 4-fold cross validation scheme. We computed the correlation between the classification results and both the kinesthetic (K) and the visual scores (V). The recovered Pearson correlation coefficient was equal to $\rho = 0.02$, (p-value = 0.87) in the first comparison, and $\rho = -0.12$ (p-value = 0.47) in the second. Moreover, we performed a Principal Component Analysis over the aforementioned three features (Figure 1A) whose analysis produced no indication of any correlation between them. Finally, we observed 3 different profiles according to users' MIQ-RS values (identified K+ and/or V+ if their score is over 70%, K- and/or V- otherwise). We computed the average accuracy of each class (Figure 1B) and performed Welch's t-test to verify the statistical significance of the differences between the average classification results. We obtained the following p-values: 0.118 between K+V+ and K-V+; 0.714 between K+V+ and K-V-; and 0.048 between K-V- and K-V+. Finally, we computed the Event-Related Spectral Perturbation (ERSP) between 5-30 Hz within each group using the EEGlab toolbox and we again compared the differences between groups. The obtained p-values were all superior to 0.01.

Discussion: Our results revealed no correlation between the classification results and the MIQ-RS scores, contrary to those suggested by [1, 3]. While the classification results and ERSPs differ upon grouping the subjects according to their MIQ-RS profiles, we found no statistical significance.

Significance: Our results demonstrate that the MIQ-RS questionnaire cannot be used to estimate the performance of a MI-BCI based on distinguishing between resting state and right-hand MI tasks.

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TOWARDS UNDERSTANDING THE INFLUENCE OF THE EXPERIMENTER ON BCI PERFORMANCE

Aline Roc [1], Léa Pillette [1,2], Fabien Lotte [1,2]

1 Potioc, Inria Bordeaux Sud-Ouest, France - 2 LaBRI, Univ. Bordeaux, CNRS, INP), France

The influence of the experimenter has been suspected but not yet studied in the field of Neurofeedback/BCIs. Further researches would be interesting to:

- Diagnose how experimenters may bias results, or potentially identify attributes that could positively impact user's experience or performance in line with recommendations about BCIs and Human Learning Principles [3]
- Extend the range of collected (and published) data about experimenters (e.g., biosocial and psychological characteristics), thus improving the replicability of experiments and the quality of meta-analyses
- Suggest several solutions to prevent potential experimenter-related biased comparisons of the results, in line with recommendations from other fields [11]

By reviewing the literature, we extracted several potential factors of the influence of experimenters (see figure). First, their characteristics (e.g., expertise, gender, expectations) may directly affect the results (e.g., biasing the design of the protocol, data collection, or interpretation) [8]. Experimenters may also affect the responses and behavior of the subject, consciously or unconsciously, via direct or indirect interactions. Such an influence was observed in teacher-student relationship [9], researcher-subject interaction in business ethics [8] or "experimenter demand effect" in social [13] or economical [7] researches. In addition, studies suggest that the perceived characteristics (e.g., gender [12]) of both experimenters and subjects can influence their behavior. Social context and trainer-trainee relationship could benefit subjects' mood, psychology, stress, confidence [5], and motivation [10] which are significant elements improving the quality of their involvement [2; 6] but may as well be a source of bias [4].

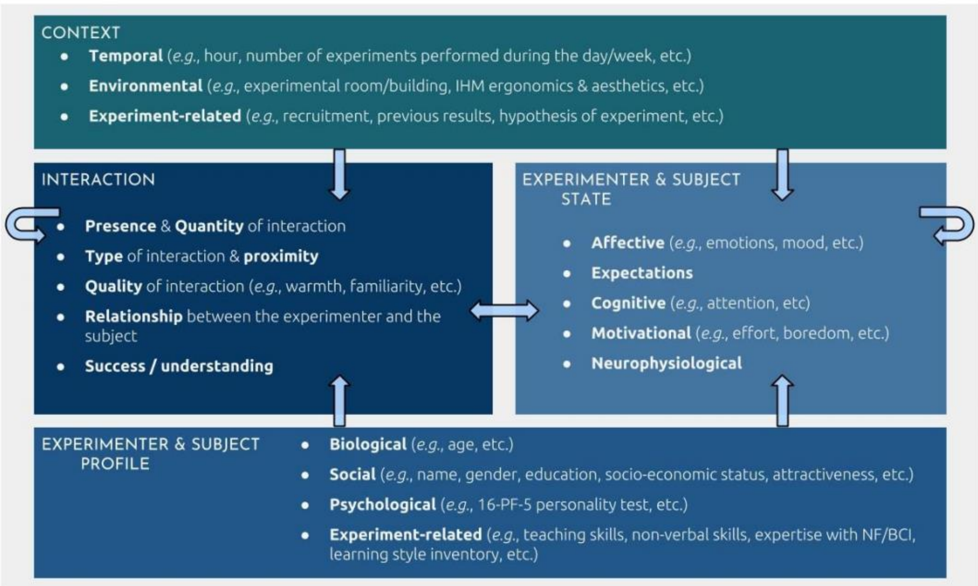

Fig. : Summary of under-investigated factors in NF/BCI studies, and how they could influence each other.

Given that the presence of a human worker is nearly inevitable, the influence of experimenters should be considered carefully while designing experiments, for instance through a better rationalization of social bias and emotional feedback [1]. This could lead to a conjoint progress of the global performance, validity and understanding of the Neurofeedback/BCI studies.

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FEASIBILITY, DESIGN AND EVALUATION OF USING BRAIN-COMPUTER INTERFACES IN AUGMENTED REALITY

Hakim Si-Mohammed [1], Jimmy Petit [1], Camille Jeunet [1,2], Ferran Argelaguet [1], Nicolas Roussel [3], Géry Casiez [4], Anatole Lécuyer [1]

1 Hybrid, Inria Rennes Bretagne-Atlantique, France - 2 CNBI, EPFL, Switzerland - 3 Inria Bordeaux Sud-Ouest, France - 4 CRIStAL, Univ. Lille, France

Brain-Computer Interfaces allow to interact with computers and systems with the sole mean of the user’s brain activity. This abstract describes the studies that we conducted on combining BCIs with Augmented Reality with the illustrative application case of a mobile robot control system. The results of 4 user studies (94 participants) are presented and discussed. First, we tested the feasibility of associating an EEG headset with an Optical See-Through Head Mounted Display (OST-HMD). The experimental results suggest the EEG and OST-HMD equipment (Microsoft HoloLens in our case) are well compatible. Second, we evaluated the effect of head movements on the recognition accuracy of steady-state visual evoked potentials (SSVEP) when interacting in AR. Our results showed a significant deterioration of the accuracy with the increase of movement intensity. However, they also suggest the possibility to detect SSVEPs under small head movement conditions. In a third time, we proposed a design space of the possible display strategies for 3 ssvep targets (representing the possible robot commands) in a 3D Augmented Reality environment. Based on five dimensions, we proposed 32 different display strategies that we evaluated through an online questionnaire in which 42 participants took part. The participants had to evaluate the coherence/intuitiveness of each one of the 32 display strategies using a 7-scale Lickert scale ranging from reject to excellent. A majority judgment procedure enabled us to rank and cluster the strategies in 4 groups with different majority grades. Lastly, we evaluated the effect of the display strategy on the SSVEP recognition accuracy in a 24 participants' user study. Even though a significant effect of changing the display strategy was found on the classification accuracy, no significant difference was found between the conditions using a standard display strategy and the best-ranked one.

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ZERO-CALIBRATION C-VEP BCI USING WORD PREDICTION: A PROOF OF CONCEPT

Federica Turi, Nathalie T.H. Gayraud, Maureen Clerc

Inria Sophia Antipolis-Mediterranée, Université Côte d'Azur, France

Brain Computer Interfaces (BCIs) based on visual evoked potentials (VEP) [1] allow for spelling from a keyboard of flashing characters. In particular, code-modulated VEP BCIs (c-VEPs) are designed for high-speed communication [2]. In c-VEPs BCI, all characters flash simultaneously, but each character flashes according to a predefined binary m-sequence [3], circular-shifted by a different time lag. For a given character, the m-sequence evokes a VEP in the electroencephalogram (EEG) of the subject [4], which can be used as a template (figure 1a). After a predefined number of repetitions, the system estimates the time lag with respect to this template and uses it to display the desired character. The template is usually obtained during a calibration phase. In this work we propose an unsupervised method that avoids the calibration phase, by extracting from the VEP relative lags between successive characters, and predicting the full word using a dictionary. We test it in offline experiments on a dataset of 9 subjects [4]. Each experiment simulates the spelling of a 3-letter word and is parameterized by the number of repetitions of the m-code flashes. We compare our results to a calibrated experiment. In figure 1b, we see that the zero-calibration method achieves good accuracy values, even with only 8 repetitions. In comparison, the experiments preceded by calibration reach good accuracy values after 12 repetitions. We distinguish two groups of subjects: in green, those that perform well, reaching on average an accuracy value that exceeds 65% after 8 repetitions and goes up to 85% for 20 repetitions; in red, those who don't obtain more than 50%. While some subjects reach accuracy values equal to 100% after the calibration, others perform poorly, even compared to the zero-calibration method. These preliminary results show that a word prediction-based zero-calibration method in c-VEP BCIs can be efficient.

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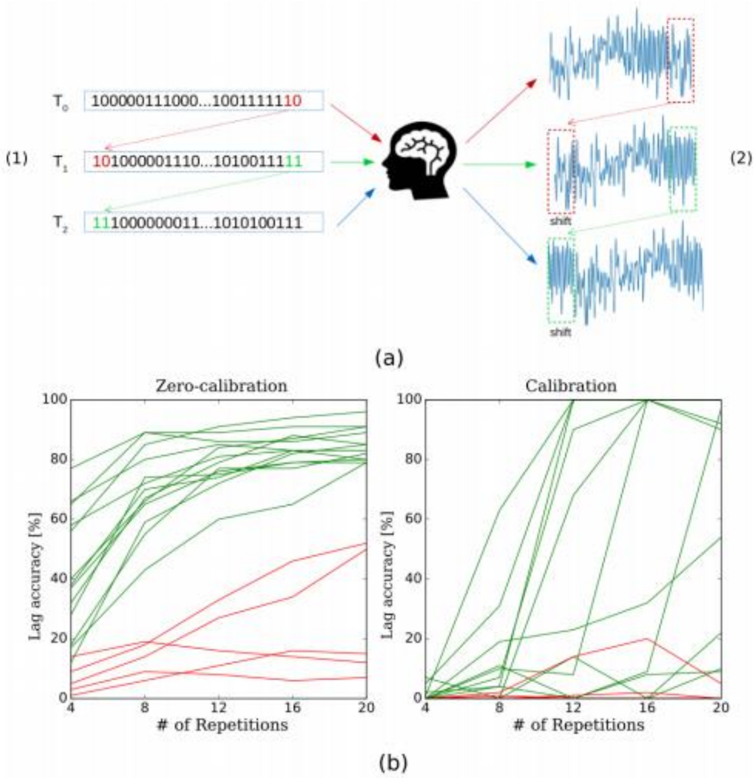

Figure 1: (a) An illustration of the generation of c-VEP responses. (a.1) The m-sequence circular-shifted by a 2-bit lag for each target. (a.2) The evoked response of each target. (b) Average lag accuracy over all experiments for each subject and session, showing how many times each method is able to recover all the correct lags within a single word. Subjects that perform well with the zero-calibration method are colored in green while those that perform poorly in red, the same subject has the same color in the two plots.

ABSTRACTS DES DISCUSSIONS THEMATIQUES

Each session will last around 30 minutes and will be articulated around talks and discussions with the audience.

SESSION #1

BCIs for Human-Computer Interaction

Chair: Hakim Si-Mohammed
Speakers: Grégoire Cattan, Sylvain Chevalier & Sébastien Rimbert

Brain-Computer Interfaces are not new. Since the first experiments on the subject, many works have tried to apply them, with relative success, to the rehabilitation of disabled persons. Although there is now a trend towards the use of BCIs in larger public contexts (VR, AR, HCI), most of the work done is not beyond the prototype and laboratory stage. What are the scientific and practical barriers that prevent BCI technology from going beyond this stage? What is missing from BCIs to represent a viable alternative means of interaction, and what should be the roadmap for researchers and industrials to lift these locks? These will be the questions asked to our panelists during this CORTICO session.

SESSION #2

The future of Open-source BCI softwares

Chairs: Fabien Lotte & Maureen Clerc
Speakers: Anton Andreev, Aurélien Appriou & Takfarinas Medani

A number of free and open-source software are available to design and use real-time BCI systems, or to study EEG signals classification in BCI. This session will be dedicated to discussions around the future of some of them. In particular, it will first present the future of the most used BCI software in France, OpenViBE, by introducing and discussing the OpenViBE consortium, a new management structure that aims at ensuring a long-term support and evolution of OpenViBE, and enabling the whole OpenViBE community to be in charge of it. This session will then present some recent extensions of the software developed at the GIPSA-Lab to increase its functionalities as well as the SIGMA Box, a matlab toolbox for offline classification of EEG signals developed by the ESPCI. Finally, a new developing Python software - BCPy - designed for easy offline classification of EEG signals - will be briefly presented.