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A Brain computer interface is an interface that let you control an application or a machine with your brain signals. Several paradigms are accepted and used commonly in the research world of BCI such as Motor Imagery, SSVEP or P300 but a new paradigm appeared a few years ago and imposed as a very powerful paradigm: the Code Visual Evoked Potential (CVEP) and several articles were written about it [[1]](#footnote-1). A new paradigm inspired from CVEP was introduced by Cabrera Castillos [[2]](#footnote-2) called Burst-VEP and use code of flashes as CVEP but the flashes are more spaced between themselves. But a problem in all paradigms for the BCI are the high inter and intra variability between subjects and sessions [[3]](#footnote-3),and a calibration time is necessary every time you want to use the BCI.

To compensate this high variability and avoid as much as possible the calibration time, using a Transfer learning technic is really recommended. Several technics were developed. For example, Ying et al [[4]](#footnote-4) are using Riemannian geometry and a training accuracy-based subject selection (TSS) with a MDM classifier to choose the best subject to train the target on. L. C. Rodrigues introduced a techniques of data alignment, data alignment is advised when doing a transfer learning, called Riemannian Procrustes Analysis (RPA) that align the distribution on the Riemannian manifold with only translations, rotations, and scaling [[5]](#footnote-5). In Thielen [[6]](#footnote-6) introduced a new method to classify without any calibration time that use the classification of long and short flashes and reconvolution.

Cabrera Castillos, Kalou, Simon Ladouce, Ludovic Darmet, et Frédéric Dehais. « Burst c-VEP Based BCI: Optimizing stimulus design for enhanced classification with minimal calibration data and improved user experience ». *NeuroImage* 284 (15 décembre 2023): 120446. https://doi.org/10.1016/j.neuroimage.2023.120446.

Coelho Rodrigues, Pedro Luiz, Christian Jutten, et Marco Congedo. « Riemannian Procrustes Analysis : Transfer Learning for Brain-Computer Interfaces ». *IEEE Transactions on Biomedical Engineering* 66, no 8 (décembre 2018): 2390‑2401. https://doi.org/10.1109/TBME.2018.2889705.

Martínez-Cagigal, Víctor, Jordy Thielen, Eduardo Santamaría-Vázquez, Sergio Pérez-Velasco, Peter Desain, et Roberto Hornero. « Brain-Computer Interfaces Based on Code-Modulated Visual Evoked Potentials (c-VEP): A Literature Review ». *Journal of Neural Engineering* 18, no 6 (26 novembre 2021). https://doi.org/10.1088/1741-2552/ac38cf.

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Thielen, J., P. Marsman, J. Farquhar, et P. Desain. « From Full Calibration to Zero Training for a Code-Modulated Visual Evoked Potentials for Brain–Computer Interface ». *Journal of Neural Engineering* 18, no 5 (avril 2021): 056007. https://doi.org/10.1088/1741-2552/abecef.

Ying, Jiahui, Qingguo Wei, et Xichen Zhou. « Riemannian Geometry-Based Transfer Learning for Reducing Training Time in c-VEP BCIs ». *Scientific Reports* 12, no 1 (14 juin 2022): 9818. https://doi.org/10.1038/s41598-022-14026-y.

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2. Kalou Cabrera Castillos et al., « Burst c-VEP Based BCI: Optimizing stimulus design for enhanced classification with minimal calibration data and improved user experience », *NeuroImage* 284 (15 décembre 2023): 120446, https://doi.org/10.1016/j.neuroimage.2023.120446. [↑](#footnote-ref-2)
3. Simanto Saha et Mathias Baumert, « Intra- and Inter-subject Variability in EEG-Based Sensorimotor Brain Computer Interface: A Review », *Frontiers in Computational Neuroscience* 13 (2020), https://www.frontiersin.org/articles/10.3389/fncom.2019.00087. [↑](#footnote-ref-3)
4. Jiahui Ying, Qingguo Wei, et Xichen Zhou, « Riemannian Geometry-Based Transfer Learning for Reducing Training Time in c-VEP BCIs », *Scientific Reports* 12, no 1 (14 juin 2022): 9818, https://doi.org/10.1038/s41598-022-14026-y. [↑](#footnote-ref-4)
5. Pedro Luiz Coelho Rodrigues, Christian Jutten, et Marco Congedo, « Riemannian Procrustes Analysis : Transfer Learning for Brain-Computer Interfaces », *IEEE Transactions on Biomedical Engineering* 66, no 8 (décembre 2018): 2390‑2401, https://doi.org/10.1109/TBME.2018.2889705. [↑](#footnote-ref-5)
6. J. Thielen et al., « From Full Calibration to Zero Training for a Code-Modulated Visual Evoked Potentials for Brain–Computer Interface », *Journal of Neural Engineering* 18, no 5 (avril 2021): 056007, https://doi.org/10.1088/1741-2552/abecef. [↑](#footnote-ref-6)