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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]. A new paradigm inspired from CVEP was introduced by Cabrera Castillos in [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],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, in [4] Ying et al 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]. In [6], Thielen et al introduced a new method to classify without any calibration time that use the classification of long and short flashes and reconvolution.

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