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# Independent linear discriminant analysis : The first step in including covariates in EEG classification

David Trocellier<sup>1\*</sup>, Bernard N’Kaoua<sup>2</sup>, Fabien Lotte<sup>1</sup>

<sup>1</sup> Inria center at the university of Bordeaux/ LaBRI, Talence, France

<sup>2</sup> Univ. Bordeaux, Bordeaux, France

The classifiers commonly used in BCIs do not take into account covariates such as changes in users’ mental states, eg., motivation or fatigue, which can influence EEG dynamic [1] and affect classification performances. We propose a linear discriminant analysis (LDA) variant [2] to account for these interfering covariates and improve performance.

LDA aims to reduce the input variables dimension while separating them into classes by linearly combining them. Our method, named independent LDA (iLDA), takes as input a vector of  $x_i$ , which is an original variable  $x$  to which we subtracted the linear influence that the vector of covariates  $z$  has on  $x$ , using linear regression, see equation 1. This allows us to reduce the influence of the covariates on the input variables by projection.

$$x_i = x - (A * Z + b)$$

*Equation 1.  $x$  is the original input variable,  $x_i$  is the variable where the linear influence of the multiple covariates in vector  $Z$  was removed,  $A$  and  $b$  are respectively the vector of regression coefficients and the error term of the linear regression predicting  $x$  from  $Z$ .  $A$  is the average regression weight estimated for each class.*

Evaluations were performed on (1) simulated data where each variable follows a normal distribution with covariates having a linear influence on all of them. (2) cross session motor imagery data, where subjective mental states measures (eg. effort or fatigue) were used as covariates. The used EEG features were CSP and band power. Three classifiers were compared: a standard LDA, an LDA with the covariates added as input variables (covLDA), and our iLDA. Results are synthetized in table 1.

Results on simulated data showed the interest of considering covariates in classifiers. This interest was not demonstrated for cross-session EEG with mental state covariates. Our next step is to test such algorithms with cross-subject EEG data and covariates (e.g., mu rhythm at rest) that are known to influence this condition.

	LDA	covLDA	iLDA
simulated data (nb_variable : 2, nb_covariable : 1)	0.741044	0.791864	0.79354
simulated data (nb_variable : 6, nb_covariable : 1)	0.941012	0.945108	0.945460
simulated data (nb_variable : 15, nb_covariable : 1)	0.996468	0.996616	0.996592
simulated data (nb_variable : 2, nb_covariable : 5)	0.736560	0.755176	0.759572
simulated data (nb_variable : 6, nb_covariable : 5)	0.942076	0.942524	0.942776
simulated data (nb_variable : 15, nb_covariable : 5)	0.996440	0.996416	0.996420
simulated data (training	0.942076	0.942524	0.942776
real EEG data : 6 CSP	0.655976	0.643288	0.646519
real EEG data : Band power features	0.608279	0.592152	0.597999

*Table 1. Accuracy performances of the three classifiers (an LDA, an LDA with the covariates added as input variables (covLDA), and our iLDA), compared in three different condition.*

## References :

- [1] U. Talukdar, et al. « Adaptation of Common Spatial Patterns based on mental fatigue for motor-imagery BCI », *Biomedical Signal Processing and Control*, vol. 58, p. 101829, avr. 2020,
- [2] P. Xanthopoulos, et al. « Linear Discriminant Analysis », in *Robust Data Mining*, Éd. New York, NY: Springer, 2013, p. 27-33.