SUPPLEMENTAL MATERIAL: R computation details

RGMM were implemented in R by adding a Ridge regularization term νI to the covariance matrix Σ_c, where the parameter ν has been tuned using a 5-fold cross-validation. HDDA method [2] has been implemented thanks to the R package *HDclassif* [1]. Implemented using the R package *e1071* [7], SVM require the setting of the kernel scale parameter and the soft margin cost, tuned by a 5-fold cross-validation. Random Forest method has two parameters to be tuned: the number of trees in the forest and the Bagging number of variables. We decided to set the number of trees to 500, and the Bagging parameter was tuned by a 5-fold cross-validation [5]. The Random Forest method was implemented thanks to the R package *randomForest* [6]. As there is no standard R package to implement FMLM, we made our own functional adaptation of the multinomial logit model in decomposing the data on a cubic spline basis (degree 3) [10], then applying the standard multivariate multinomial logit model on the obtained coefficients (we used the R package *splines* [8] to compute the cubic spline basis and the R package *nnet* [11] to build the multinomial logit model). The spline decomposition requires the choice of the number of pieces of polynomial functions (or the number of knots), tuned by a 5-fold cross-validation. NPFD requires the choice the pseudometric δ, the k-nearest neighbours parameter k and the kernel function K (the original R implementation codes of the NPDFA method are freely available online at `http://www.math.univ-toulouse.fr/~ferraty/`. We made an adaptation the function *funopadi.knn.lcv* in order to make global the automatic choice of the k-nearest neighbours parameter k by a 5-fold cross-validation. However, Ferraty and Vieu [4] showed that the choice of the kernel function K has a negligible impact on the NPFD estimator's convergence rate compared to the the pseudometric δ and the k-nearest neighbours parameter k; thus, we arbitrarily fixed it as the standard quadratic kernel. Among several others, we chose in this study δ as the MPLSR (Multiple Partial Least Squares Regression) pseudometric, because it seems to be particularly adapted for hyperspectral data classification [12]. FSVM is based on an approach proposed by Rossi and Villa [9], computing the standard SVM on the coefficients of functional data decomposition by a cubic splines basis. FRF applies a Random Forest approach for functional data classification, decomposing the data on a cubic splines basis, then applying the standard Random Forest on the obtained coefficients. For both last methods, parameters have been tuned by a 5-fold cross-validation in the same way than their multivariate version.

References

[1] L. Bergé, C. Bouveyron, and S. Girard, *HDclassif: An R Package for Model-Based Clustering and Discriminant Analysis of High-Dimensional Data*, Journal of Statistical Software 46 (2012), pp. 1–29.

[2] C. Bouveyron, S. Girard, and C. Schmid, *High-Dimensional Discriminant Analysis*, Communications in Statistics - Theory and Methods 36 (2007), pp. 2607–2623.

[3] G. Fan, J. Cao, and J. Wang, *Functional data classification for temporal gene expression data with kernel-induced random forests*, in *IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB)*, IEEE, 2010, pp. 1–5.

[4] F. Ferraty and P. Vieu, *Nonparametric Functional Data Analysis : Theory and Practice*, New York : Springer-Verlag, 2006.

[5] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statisical Learning - Data Mining, Inference and Prediction*, Vol. 2, Springer, 2009.

[6] A. Liaw and M. Wiener, *Classification and Regression by randomForest*, R news 2 (2002), pp. 18–22.

[7] D. Meyer, E. Dimitriadou, K. Hornik, A. Weingessel, and F. Leisch, *e1071: Misc Functions of the Department of Statistics (e1071), TU Wien* (2012), r package version 1.6-1.
[8] R Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria (2015).
[9] F. Rossi and N. Villa, *Support vector machine for functional data classification*, Neurocomputing 69 (2006), pp. 730–742.
[10] L. Schumaker, *Spline functions: basic theory*, Cambridge University Press, 2007.
[11] W.N. Venables and B.D. Ripley, *Modern Applied Statistics with S*, 4th ed., Springer, New York, 2002.
[12] A. Zullo, M. Fauvel, F. Ferraty, M. Goulard, and P. Vieu, *Non-parametric functional methods for hyperspectral image classification*, in *IEEE International Geoscience and Remote Sensing Symposium*, IEEE, 2014, pp. 3422–3425.