Automatic Classification of Large Sets of Brain Activity fMRI Time Series

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***Abstract*—We use machine learning and information theory to analyze fMRI recordings of brain activity. These recordings provide n recorded time series mapping the activity of n parcels. To evaluate the large time series we use very large matrices of Mutual Information ($MI_{n \times n}$) between pairs of recorded time series. We generalize the MI concept to evaluate the interconnectivity matrix $MIreg$ between pairs of $m,\ m << n$ Cortex Regions Reg. The achieved matrix of size $m \times m$ with $\frac{m(m+1)}{2}$ coefficients characterizes the brain network's features. Since the number of coefficients is too large, we need to select the most significant ones. We design a deep learning algorithm to classify the patients by using some of these coefficients as the input of a neural network (NN) and introduce parsimony constraints to build a very restricted MLP to avoid overfitting.**

***Index Terms*—fMRI Time series, Machine Learning, Mutual Information, Big Data, Brain Activity**

I. Classification by Minimal Size Neural Networks

To classify the patients (.e.g Normal vs Abnormal Alzheimer classification or localization of epileptic seizure focus within one of eight cortex lobes) we use computerized analysis of cortex activity recorded via fMRI. Our innovative machine learning techniques involve intensive analysis of large matrices of mutual information coefficients between pairs of anatomically identified regions [1]–[3]. The inter connectivities generated by these regions are the input of a Parsimonious Multi-Layer Perceptron (MLP) with a highly restricted number of nodes to mitigate the currently moderate number of diagnosed patients.

II. Parameters Parsimony Constraints for MLPs

Our MLP classifiers involve 4 successive layers of artificial neurons : an input layer of size IN, a hidden layer of size HID, an internal output layer of size OUT, and finally a softmax layer of size OUT. The number W of free weights and thresholds of such an MLP is $W = HID(IN + OUT + 1) + OUT$. Call S the size of the training set. Each training case provides OUT precise values for the OUT decision probabilities computed by the softmax layer. Each case hence yields $(OUT - 1)$ equations which must be verified by the W free parameters. The training set thus provides $(OUT - 1) \times S$ non linear equations to be satisfied by W unknowns. To avoid overfitting one should have the following Parameters Parsimony Constraint on HID and IN:

$$HID(IN + OUT + 1) < (OUT - 1)S - OUT.$$

III. Input selection for minimal size MLP classifiers

For feature F and patient PAT the corresponding value $F(PAT)$ is computable, now each class $CL(p)$ generates an interval

$J_p(F)$= smallest interval containing all the $F(PAT)$ for $PAT \in CL(p)$.

The separability of $J_p(FAT)$ and $J_q(FAT)$ characterizes the discriminating power of feature F to handle the $CL(p)$ vs $CL(q)$ task. The features with the highest discriminating power form the input of the MLP.

In our data set of S=55 epileptic patients: n=1500, m=148, $IN\ \leq$18, HID=7, OUT=5 for localization of epileptic seizure focus within one of the most common five cortex lobes. The trained MLP shows a successful leave-one-out performance of 90% [4].

IV. Conclusion

The combination of Information Theory and Deep Learning algorithms such as MLP provide a strong tool to evaluate the brain activity. Because of ”Big Data” nature of the brain activity time series (huge feature space) and because of the small number of the patients, the parsimony constraints should be taken in account to train a robust and valid neural network.

References

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