

# Machine Learning to Evaluate fMRI Recordings of Brain Activity in Epileptic Patients

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**Short Abstract** — We analyze fMRI recordings of brain activity in epileptic infants. These recordings provide roughly 1500 recorded time series mapping the activity of 1500 very small cortex patches. The ultimate goal of our study is to facilitate noninvasive localization of the epileptic focus. We have implemented several Automated Classifiers of fMRI recordings into 5 classes of patients. Here we outline how one can use a Multi-Layer Perceptron (MLP) with highly restricted number of nodes to mitigate the currently small number of diagnosed patients. We introduce a novel multiscale analysis to select Cortex Regions with high discriminating power between patients classes. Another key point is our systematic use of very large matrices of Mutual Information (MI) between pairs of recorded time series. We generalize the MI concept to evaluate the interactivity between pairs of cortex regions of arbitrary size. Our MLP classifier performance is quite good, but will need validation on larger data sets.

**Keywords** — fMRI Brain Recordings, Robust Classifiers, Deep Learning, Mutual Information, Epilepsy Focus.

## I. MUTUAL INFORMATION AND REGIONAL CORTEX CONNECTIVITY

An ongoing study at Texas Children's Hospital gathers sequences of fMRI 3D-images recording cortex activity for young epileptic patients [1]. Each fMRI recording generates 295 3D-images algorithmically registered onto a pre-segmented cortex atlas and thus partitioned into 780 disjoint "parcels", 148 "cortex regions", and 10 "lobes".

For each patient, there are roughly 780 cortex parcels and fMRI data provide for each parcel one time series with 295 points. To characterize brain interactivity, we compute for each patient the 780 x 780 matrix of Mutual Information  $MI(m,n)$  between all pairs of time series. MI quantifies non-linear information links between two time series and has often outperformed correlations in the analysis of cerebral activity [2].

We have 148 anatomically identified cortex regions  $R_j$ . We quantify the "connectivity"  $c(R_j)$  of any region  $R_j$  by computing the 75% quantile of all the  $MI(m,n)$  corresponding to parcels "m" and "n" belonging to  $R_j$ . This defines a vector  $V$  of 148 regional connectivities  $c(R_j)$ . Each

patient  $Pat_k$  is characterized by its vector  $V_k$  of regional connectivities.

Diagnosed patients belong to 5 classes defined by the epileptic focus localization, positioned by neuro-surgeons within 5 distinct large cortex zones. Our database provides 19 diagnosed and 13 non-diagnosed patients. This very restricted dataset imposes a strong parsimony for the number of parameters in our classifier. So even moderately large MLPs are not usable, because they involve large numbers of unknown weights. We radically reduce the input dimension for our MLP by selecting highly discriminating cortex regions. We also minimize the size of our MLP classifier to ensure robustness of classification.

## II. HIGHLY DISCRIMINATING CORTEX REGIONS

Fix any two classes  $CL_p$  and  $CL_q$ . For any region  $R_j$ , we quantify its power to discriminate  $CL_p$  vs  $CL_q$  by comparing the distributions of  $c(R_j)$  values for patients in  $CL_p$  and patients in  $CL_q$ . Call  $S_{p,q}$  the region having highest power to discriminate  $CL_p$  vs  $CL_q$ . The 10 pairs  $CL_p$  vs  $CL_q$  thus generate 10 cortex regions  $S_{p,q}$ . For each patient, the vector of 10 connectivities  $c[S_{p,q}]$  becomes the short input for our MLP classifier, for which we impose a single hidden layer of size 5 to minimize the number of MLP parameters. After automatic learning the classification performance estimated by "leave-one-out" is 93% +/- 3%.

## III. CONCLUSION

We introduce and test efficient new methods to implement robust classification for fMRI recordings of brain activity.

## REFERENCES

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