Voxel Selection of fMRI Data using Multi- Voxel Pattern Analysis to Predict Neural Response

[1]Swathi C M, [2]Thippeswamy K H
[1]MTech in Digital Electronics, [2]Assistant Professor
[1]Department of Electronics and Communication,
[1]Don Bosco Institute of Technology, Bangalore, India

***Abstract*— fMRI system shows that all the information of the brain that is represented in the subject of the brain at a particular point in time. The MVPA approach has lead to several impressive facts of brain reading. fMRI data uses Multi-voxel pattern analysis (MVPA) approach to relate the neural activities to cognition. A challenging factor is to build a generalizable classification model because the number of voxels (features) always exceeds the total number of stimulus/data observations, creating model overfitting. Thus selecting informative voxels should be done before constructing a classification model. In this paper, we propound an effective feature (voxel) selection strategy using partial least square regression (PLS) to form an index for the informative voxels to prioritize the voxel selection based on the degree of association to the stimulus conditions.**

***IndexTerms*—** Multi-voxel pattern analysis (MVPA), functional magnetic resonance imaging (fMRI), partial least square (PLS).

I. INTRODUCTION

fMRI was developed in the 1990 by Seiji Ogawa which use oxygen metabolism and blood flow to extrapolate brain activity. Functional magnetic resonance imaging (fMRI) is a neuroimaging procedure that computes the activity of brain depending on the changes in the flow of blood. The MRI scanner contains an electro-magnet which has field strength of 3tesla (3T). When a particular region of the brain is activated, blood flow to that region also increases. Voxels also called *volume pixels* are the smallest recognizable square-shaped part of a three-dimensional image. The activity concerned to a voxel is expounded as how proximate the expected time-course matches the time-course of the signal. Multi-Voxel Pattern Analysis (MVPA) is a statistical technique used in the analysis of fMRI images. It is to set up a pattern classification model of BOLD responses from the entire brain or confined to a particular brain region of interest (ROI) to estimate the degree of association of cognition with the experimental conditions (e.g., visual stimuli). One of the exploring researches of MVPA was executed where multi-voxel patterns were considered in the ventral temporal (VT) cortex in retaliation to various groups of visual stimuli. To identify and prioritize the voxels in the VT cortex which are associated with object- level representations, Partial Least Square (PLS) Regression is used. Partial Least Square (PLS) regression is a multivariate statistical measure used to identify the latent information in the multivariate patterns guiding the selection of feature sets of informative voxels.

II. EXISTING METHOD

A standard survey of fMRI data depends on univariate statistics (e.g., comparing task conditions), where the response at each location in brain is considered independently. However, recent studies have demonstrated that many “mental representations” may in reality be lodged in a distributed neural populace recorded in the activity pattern across multiple voxels [2], [3] and [4]. The changes in the activity of neurons are assumed to be hypothetically induced, with fMRI time series data which contemplates the response to stimuli at definite locations (i.e., voxels) across the brain.

In the unvariate system, the hemodynamic response combined to neural activity is at a slow-pace (i.e. in the order of seconds) which allows the change in the observed BOLD signal associated with a particular stimulus (or stimulus block) be modeled by a canonical response function and encapsulated by a single value. The disadvantages of the existing system are as follows:

- Since single voxel is considered at a time, the computation time is more.
- A univariate model is less comprehensive compared to multivariate model. In real world, there is often more than one factor at play and a univariate model is unable to take this into account due to its inherent limitations.

III. PROPOSED APROACH

A. Block Diagram

Multi- Voxel Pattern Analysis has been most commonly used to perform classification of “cognitive representations” into discrete categories of stimulus conditions. This subset of MVPA entails three methods: Feature extraction, Feature selection, and Pattern classification, where *features* are commonly called *voxels*. Feature extraction is a method to distinguish the temporally- changing BOLD response at a voxel to a stimulus. The most common approach is to calculate the measure of the response of fMRI data for each stimulus event or block by implementing a hemodynamic response function convolved with an impulse or a box-car regressor in the general linear model (GLM).

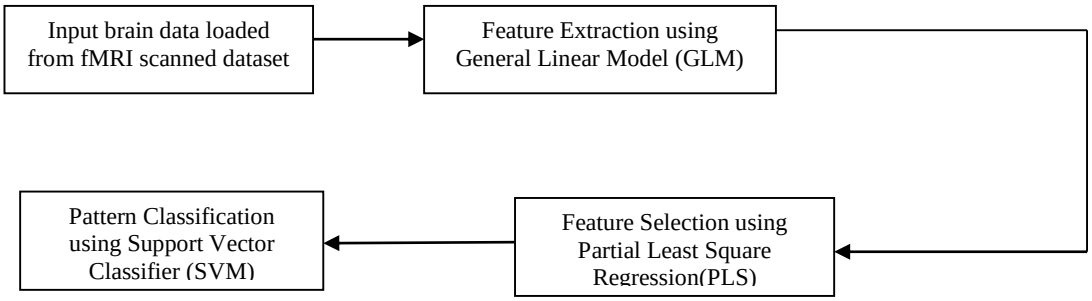

Figure 1. Block diagram of proposed system

Feature selection is a method to recognise and select the subset of voxels to employ with the classification model. Technically, this step is extremely crucial as the selected features are explained as studying the anatomical regions supporting the cognitive processes. Pattern classification is a method to train a classification algorithm to generate a presage classification model that best isolates the stimulus categories within the multidimensional space interpreted by the selected features (voxels).

B. General Linear Model (GLM)

The general linear model is a statistical linear model. It may be written as

$$\mathbf{Y} = \mathbf{XB} + \mathbf{U} \qquad (1)$$

where **Y** is a matrix with series of multivariate measurements, **X** is a matrix that might be a design matrix, **B** is a matrix containing parameters that are usually to be estimated and **U** is a matrix containing errors or noise. The errors are usually assumed to be uncorrelated across measurements, and follow a multivariate normal distribution. If the errors do not follow a multivariate normal distribution, generalized linear models may be used to relax assumptions about **Y** and **U**.

C. Partial Least Square Regression (PLS)

Partial least square (PLS) is a method for constructing predictive models when the factors are many and highly collinear. The PLS regression can be related to the matrix of extracted β weights as follows. Consider a data matrix, whose size is A x B, where A is the total number of data instances and B is the number of voxels, and matrix Y, whose size is A x P, where A is the total number of data instances and P is the number of dependent variables. The PLS regression model is then be manifested as,

$$y_{ic} = b_{cj}x_{ij} + \epsilon_{ic} \qquad (2)$$

where b_{cj} are the regression coefficients that depends on the association among all the features giving a better estimation of the dependent variables and ϵ_{ic} are the residuary errors. The objective of PLS is to build a small number of independent and linear combinations of features

IV. EXPERIMENTAL RESULTS

In this case study, we employed fMRI data of one context from the study basically brought out by Haxby et al. [1]. The dataset embeds 10 fMRI runs with each run comprising of eight stimulus blocks as seen in fig. 2(b). One image of activity of brain in the dataset (i.e. 64x64x40 voxels) was obtained every repetition time (TR) of 3s, and there are a total of 8 TRs in each block. Thus there are 640 data instances in total (10 runs x 8 blocks x 8 TRs).

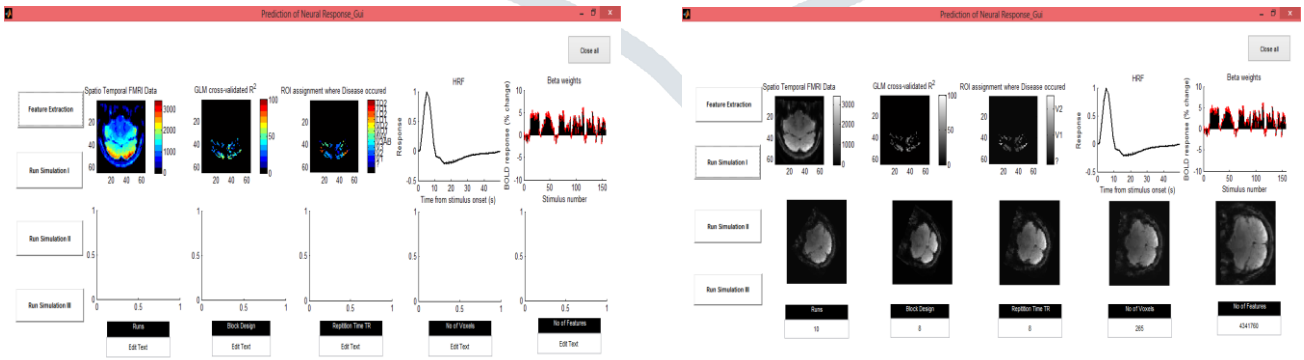

Figure 2.(a) Feature Extraction using General Linear Model (b) Brain Dataset is loaded and the total numbers of features are extracted.

In our study, we made use of ROI in the VT cortex explained by functional anatomic criteria [1]. In addition, we extended our analysis to the entire brain space that enfolds a total of 43,41,760 voxels. To identify the temporally-changing BOLD signal with respect to a given stimulus, GLM is applied, and coefficient parameters β are calculated by fitting a GLM with distinct predictors for each stimulus block as seen in fig. 2 (a). The weights (parameters) are extracted for each run of the test, each producing a 3-Dimensional (3-D) weight matrix for every voxel, which can then be modified to a 2-D feature matrix. For further computation of data it is converted to grayscale, as the computation becomes easier on a grayscale basis. Also the total number of features present in the entire brain is calculated as seen in fig. 2 (b). The comparison of the estimated value of the latent variable using PLS is done

with the canonical value leading to a plot as seen in fig. 3 (a). For the huge number of features, the informative voxels are estimated and a classification of the class label and the feature is done as seen in fig. 3 (b).

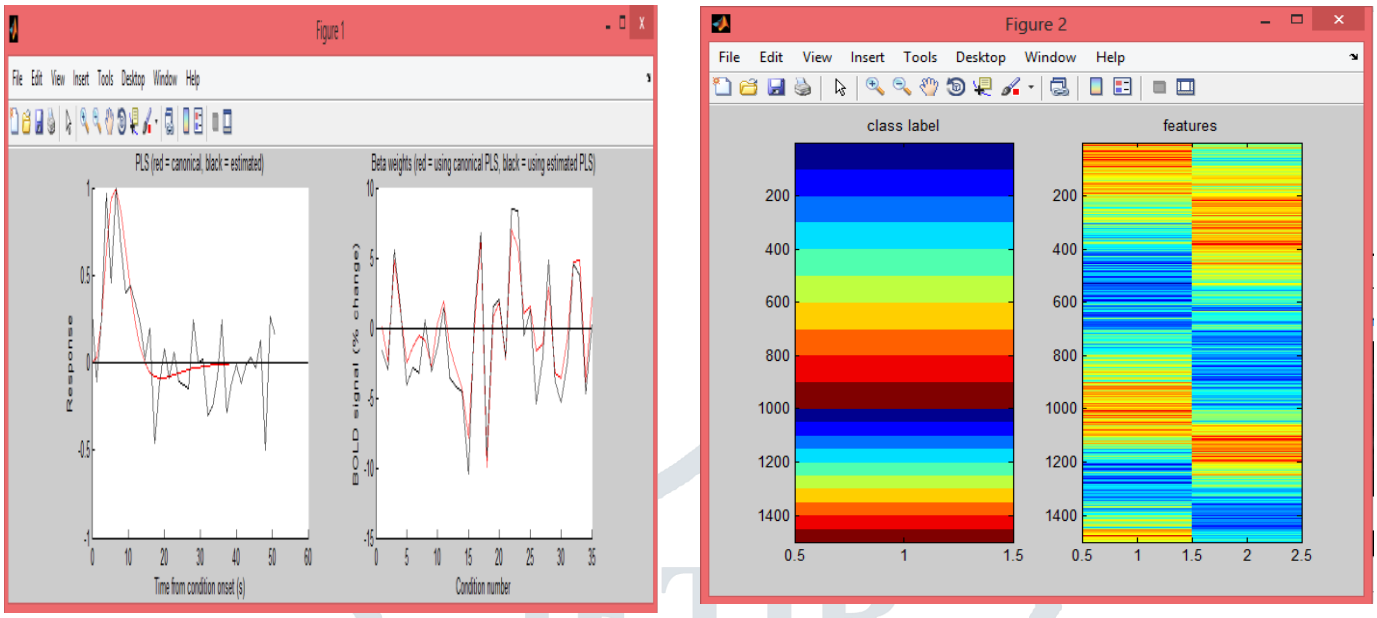

Figure 3.(a) Comparison of estimated and the canonical values of beta weights and the PLS (b) Class label and the features used for classification.

V. CONCLUSION

In this paper, we present a new voxel priority designation and selection chassis that trains voxels according to the degree of association to the experimental conditions. PLS regression was proposed to attain and create informativeness indexes to select voxels, before constructing a classification model in MVPA. Using a criterion fMRI dataset [1], we signify the advantage of our approach to determine the impact of feature selection. The proposed selection strategy guaranteed insertion of the best selection of informative voxels which will be used in the classification model, limiting the set of voxels under contemplation to a functional-anatomic defined region.

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