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Multiclass Classification of fMRI using Linear Collaborative Discriminant Regression Classifier

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Abstract— In this paper, a hybrid GA-LCDRC model is proposed to address multiclass functional MRI classification problem. KNN based genetic algorithm is used as the feature selector and linear collaborative discriminant regression classifier (LCDRC) is used as the classifier. The effectiveness and usefulness of this model is assessed based on its classification specificity, sensitivity and accuracy. This approach is tested to Haxby's 2001 functional MRI dataset with eight different classes. The result indicates that the proposed hybrid model can be used for multiclass cognitive state classification.

Keywords— fMRI, multiclass, linear collaborative discriminant regression classifier (LCDRC), genetic algorithm

I. Introduction

In medical image processing, fMRI (Functional Magnetic Resonance Imaging) recognition is challenging issue. It is very influential area with large number of practical applications such as early diagnosis of any mental diseases, determining behavioral interventions etc. Many researchers are working in this field to find accurate and appropriate algorithms to address above applications. Some of the algorithms are Support Vector Machine (SVMs), K-Nearest neighbor (KNNs), Naive Bayes (GNB), Logistic regression (LR) etc. [1-2]. The main objective of all these algorithms is to boost the accuracy of recognition to the acceptable level. The essential factor in boosting the accuracy of fMRI recognition is selection of appropriate features. This selection requires that, each feature must be distinct enough to differentiate classes for classification.

In this paper, we present a hybrid GA-LCDRC model for multiclass fMRI classification where the KNN based genetic algorithm is used to address features selection and dimensionality reduction issue and linear collaborative discriminant regression classifier (LCDRC) [3] for multiclass classification issue. The proposed methodology is tested on Haxby's faces and objects fMRI dataset. Figure 1 shows the category specificity of patterns of response. Brain images shown here are the normalized patterns of response in two axial slices in a single subject. For each pair wise comparison, the within-category correlation is compared with one between-category correlation [4].

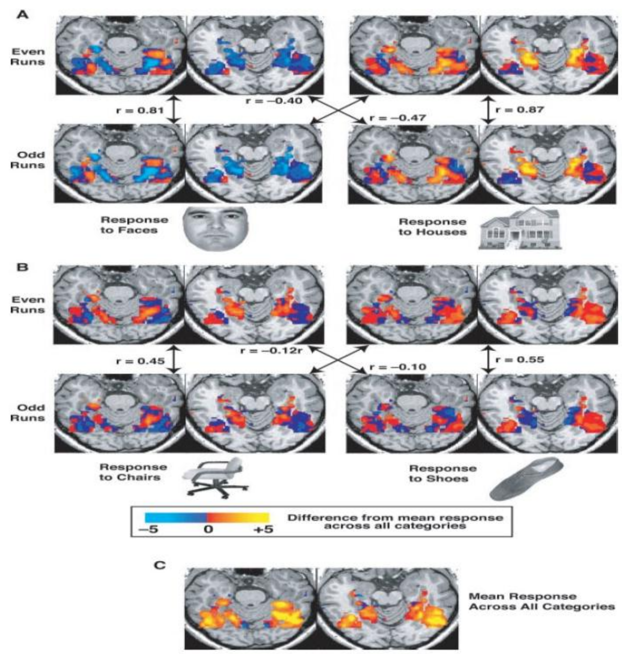

Figure 1. Sample from Haxby's dataset [4]

Rest of the paper is organized as follows, Section I contains the introduction of fMRI study and various algorithm evolved for classification, Section II contain the related work of fMRI classification, Section III contain the description of proposed methodology, Section IV contain the experimental results on multiclass dataset, section V concludes research work.

II. Related Work

There are different kinds of studies conducted for classification of fMRI data. This section presents some of the past studies.

Muhammad et. al. [5] proposed Anatomical Pattern Analysis (APA), this framework was new feature extraction method with AdaBoost as binary classification. This study was conducted on 4 categories viz. “words”, “consonants”, “objects” and “scrambled photos”. This methodology was also applied for multiclass classification of 8 classes and 4 classes producing around 59% and 95% accuracy respectively.

Ludmila et. al. [6] proposed random subspace (RS) ensemble methodology for classification of fMRI. Random subspace fragmented original set of features and framed one classifier on each subject. Majority voting and average output probabilities were used to assign labels to a class. This methodology was tested on Haxby’s dataset, and two other datasets collected in house Bangor 1 and Bangor 2. They found that random subspace with SVM as the base classifier performed well against Adaboost, bagging, rotation forest and random forest.

Halthor et. al [7] proposed univariate and multivariate feature selection method. They used principal component analysis (PCA) and image smoothing with support vector machine (SVM) without kernel for classification of fMRI data. Their method produced 93.16% accuracy.

Loula et. al. [8] proposed a new framework which was use to separate the spatial and temporal components. These components were produced by decoding the fMRI time-series in each scan. Their model performed better than standard approaches on haxby’s dataset, mirror reversed text data, textured dataset, and temporal tuning dataset.

Sun et al [9] proposed a hybrid model of convolutional neural networks (CNNs) and support vector machines (SVMs). They used CNN as feature extractor and SVM as classifier. They used Haxby’s dataset for their experimentation which achieved classification accuracy of 99.5% against Haxby’s experiment. Their paper also compares learning algorithms such as Adaboost, KNN, NN and decision tree.

III. Methodology

The block diagram for multiclass classification of fMRI dataset is shown in figure 2. fMRI data is taken from Haxby’s faces and objects database. The proposed method is based on KNN based genetic algorithm (described in section A) for feature selection. The optimal features selected in feature selection phase are used as an input vector to the linear collaborative discriminant regression classifier as described in section B. Performance of proposed method is calculated through sensitivity, specificity and accuracy.

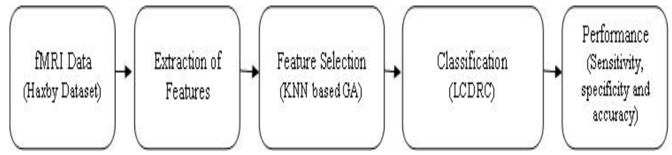

Figure 2. GA-LCDRC Classification

A. *Feature selection using KNN based genetic algorithm*

Genetic Algorithm (GA) is used for addressing feature selection issue in this paper. Features that contribute most in the classification accuracy are selected as input features to the classification algorithm. There are many varieties of genetic algorithm available in the literature. Out of those, KNN based genetic algorithm is used for current study. The step by step procedure of KNN based genetic algorithm is as below.

Step by step procedure of entropy based genetic algorithm

- Vector of feature/attribute values and class values for each training instance is given as the input.
- Initial population is set as the subset of input features (randomly).
- The fitness function of each individual is calculated by using K-nearest neighbor algorithm with the distance measure: Euclidean distance. The general formula of Euclidean distance is given in the equation (1).

$$\text{Euclidean distance} = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

  Where, x and y are represented as Euclidean vectors, and n is represented as the position of the Euclidean point.
- Mutation and crossover is applied to all the individuals.
- On each generation, based on KNN error value, individual for next generation is selected.
- Repeat this process until stopping criteria met (maximum generation reached).
- Feature indexed Vector are selected.
- For new set of selected feature again calculate classification of accuracy.

B. *Classification using LCDRC*

On obtaining the significant feature values, LCDRC algorithm [10] is implemented for classifying the obtained fMRI data features. At first, train the fMRI data of the $i-th$ class, as $C_i \in \Re^{S\times n_i}$, each column C_i represents S spatial to the fMRI data of i th class. The training examples from fMRI data n_i are define in vector as $i = 1,2,3,\dots t$, where t is represented as the total number of classes. Then, consider the fMRI data P using C_i and β_i , which is mathematically expressed in the equation (2).

$$P = C_i \beta_i, \quad i = 0,1,2,3,\dots,d \tag{2}$$

Where, $\beta_i \in \Re^{n_i \times 1}$ is denoted as parameter of regression, β_i is evaluated by employing the least square estimation. Mathematically, β_i is described in the equation (3).

$$\hat{\beta}_i = (C_i^T C_i)^{-1} C_i^T P, \quad i = 0, 1, 2, 3, \dots, d \tag{3}$$

Proposed $\hat{\beta}_i$ which is vector of parameters along with the predictor C_i is used to calculate the response vector of i th class. Substitute the equations (2) and (3) in equation (4).

$$\hat{P}_i = C_i \hat{\beta}_i = C_i (C_i^T C_i)^{-1} C_i^T P = H_i P, \quad i = 0, 1, 2, 3, \dots, d \tag{4}$$

Where, H_i is called hat matrix that plots P on $\hat{P}_i$. At last, the restoration error of each class is evaluated with lowest reconstruction error.

$$e_i = \|P - \hat{P}_i\|_2^2, \quad i = 0,1,2, \dots d \tag{5}$$

Classification method: LCDRC implement discriminant analysis in the Linear Regression Classification (LRC) to deliver efficient discrimination. Assuming all the fMRI data from the matrix, this is signified in the equation (6).

$$C = [C_1, \dots, C_i, \dots, C_n] \in \Re^{S \times m} \tag{6}$$

Where, m is labeled as number of fMRI data, S is represented as the spatial of data.
Therefore, the class label of C_i is stated as $l(C_i) \in \{0,1,2, \dots d\}$. In addition, the sub-space projection matrix $U \in \Re^{S \times n}$, $n < S$ is determined by projecting each C_{ij} into the learned sub-space.

$$P_{ij} = U^T C_{ij}, \text{ where, } 1 \le j \le n \tag{7}$$

For each class, mapping of entire trained fMRI data matrix is done to acquire the linear discriminant function P_i, which is denoted in the equation (8).

$$P_i = U^T C_i \in \Im^{S \times n} \tag{8}$$

Where, U^T is named as projection matrix for whole set and T represents the transformation of all classes.
We have to maximize the ratio of BCRE (Between Class Reconstruction Error) on WCRE (Within Class Reconstruction Error), Now substitute equation (8) in equation (5). Then, inter-class and intra-class variances of the training samples represented as BCRE and WCRE are denoted in equations (9) and (10).

$$BCRE = \frac{1}{n} \sum_{i=1}^{d} \sum_{j=1}^{n} \|P_i - \hat{P}_{ij}^{r}\|_2^2 \tag{9}$$

$$WCRE = \frac{1}{n} \sum_{j=1}^{n} \|P_i - \hat{P}_{ij}^{a}\|_2^2 \tag{10}$$

IV. Results and Discussion

The proposed approach is experimented using MATLAB (version 2017B) with 8 GB RAM, 2.00 GHz AMD 64 bit processor and 1 TB hard disc on haxby's dataset. For estimating the proposed methodology effectiveness, performance in terms of sensitivity, specificity and accuracy is calculated which can be represented mathematically as follows.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100 \tag{11}$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \tag{12}$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \tag{13}$$

Where, TP- True Positive, TN- True Negative, FN- False Negative, and FP- False Positive obtained through confusion matrix.

A. The Dataset

Haxby fMRI data [4] consisting of 6 subjects is used for this study. This dataset is from study on faces and objects representation on ventral temporal cortex. It consists of 12 runs per subject. For individual run, each subject was viewed grayscale pictures of 8 different categories/classes of objects viz. "faces", "cats", "houses", "chairs", "scissors", "shoes", "bottles" and "scrambled images". Objects were grouped in 24 seconds blocks with interval of rest period. Each picture was put on display for 500ms and succeeded by 1500ms interval. fMRI data of full brain were recorded with repetition time of 2.5s.

B. Results

The performance of proposed method GA-LCDRC as multiclass classification is shown in table 1. Total 6 subjects and 8 classes are considered for classification. The average sensitivity of all subjects is found to be 70.48%, average specificity is found to be 70.18% and accuracy for classification is found to be 74.00%. The graphical representation of sensitivity, specificity and accuracy is shown in Figure 3.

Table 1: Classification sensitivity, specificity and accuracy for LCDRC

Subjects	**LCDRC**		
	Sensitivity (%)	**Specificity (%)**	**Accuracy (%)**
Sub1	70.63	71.21	69.10

Sub2	77.46	74.33	80.75
Sub3	69.67	68.45	72.59
Sub4	67.78	65.55	71.62
Sub5	68.77	72.34	78.96
Sub6	68.55	69.22	70.98
Avg	**70.48**	**70.18**	**74.00**

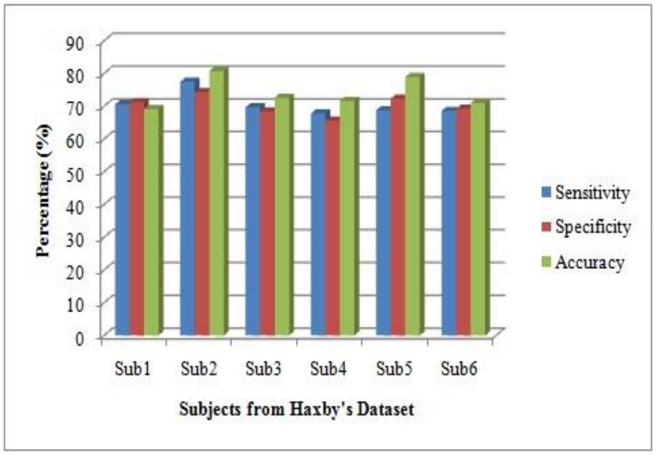

Figure 3. Sensitivity, Specificity and Accuracy on Haxby's Dataset

V. CONCLUSION

A hybrid classification method for multiclass classification of cognitive state has been proposed. The proposed methodology is a combination of KNN based genetic algorithm and Linear Collaborative Discriminant Regression Classification (GA-LCDRC). The key significance of proposed methodology is selection of optimal features from available features and classification. Based on the results of experiment, the proposed model is favorable model for classification of the cognitive states. The average classification accuracy for GA-LCDRC is 74.00% on eight classes.

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