©2010 International Journal of Computer Applications (0975 - 8887)
Volume 1 – No. 27

Pattern Classification and Analysis of Brain Maps through FMRI data with Multiple Methods

Dr H N Suma
Assistant Professor & Head
Department of Medical Electronics
BMSCE, Bangalore.

Dr Murali S
Professor & Head
Department of I S & E
PESCE, Mandya.

ABSTRACT
The activity patterns in functional Magnetic Resonance Imaging (fMRI) data are unique and located in specific location in the brain. The main aim of analyzing these datasets is to localize the areas of the brain that have been activated by a predefined stimulus [1]. The basic analysis involves carrying out a statistical test for activation at thousands of locations in the brain. The analysis is based on fMRI brain activation maps generated using the Statistical Parametric Mapping (SPM) approach. The use of individually generated activation maps with SPM allows for better scalability to very large subject pools and it has the potential to integrate data at the activation map level that would be technically difficult to combine at the raw data level.
The fMRI data is huge, dimensionally dissimilar for different orientation data and also show a lot of variation in the data acquired for different subjects for similar activities. The variations are so obvious that there are variations in the data of same subject for different trails. In this context we have explored the possibility of different Pattern Recognition Technique on same data to choose the best option. The comparison of classification efficiency of two methods implemented: The Back Propagation Neural Network Technique and The Naïve Bayesian Technique show that the two are efficient in classification of the fMRI Patterns under different contexts.

Keywords:
fMRI, Pattern Classification, Back Propagation Neural Network, Naïve Bayesian Classification

1. INTRODUCTION
Pattern classification for fMRI is to automatically identify different patterns in distributed neural substrates resulting from motor and cognitive (memory related) tasks [2]. Pattern classification of fMRI activity maps is challenging area of research due to multiple reasons. First it involves analysis of huge dataset representing each voxel of the brain 3D data in three orientations of the brain. The dimensionality mismatch of the data due to uneven anatomical structure of the brain forms the second problem. This is because most of the pattern classification methods use similar dimension datasets for classification. Third challenging area is

normalization technique for addressing the varied types of activity maps resulting from different acquisition technique. We need to generalize the analysis process of extracted activity maps which is independent of acquisition protocol. These limitations form the motivation for the research proposal on efficient fMRI data analysis methods which help in classification and recognition of activity maps rendered for different predefined tasks.We need to generalize the analysis process of extracted activity maps which is independent of acquisition protocol. These limitations form the motivation for the research proposal on efficient fMRI data analysis methods which help in classification and recognition of activity maps rendered for different predefined tasks. The limitations of the fMRI data sets are to be addressed to evolve methodologies for efficient classification and recognition of fMRI activity maps.

First the high dimensionality of fMRI data and dimensionality mismatch of data in three orientations (Axial, Sagittal and coronal) pose a main drawback for application of traditional classification algorithms: The brain data is usually acquired in three orientations. The data in each orientation is three dimensional i.e., multiple image slices of the brain are considered for all three orientation. This results in huge data. Because of the anatomical structure of the brain, the number of slices in each orientation varies. There will therefore be different slice numbers for different orientations. The motivation for research is therefore to modify the existing classification algorithms to adapt to the huge size and also to the varying dimensions of the fMRI data.

The second limitation is the small number of available data sets. The pattern classification can be performed with reference to the normal subject data. To arrive at a normal subject template multiple data sets of subjects with varying age and different habitat, which precisely means inter individual differences are to be considered. The availability of fMRI datasets of normal subjects is very sparse. With limited datasets the efficiency of classification of any algorithm will not be rightfully justified. This calls for incorporation of methods which can effectively depict the efficiency of classification even with few datasets.

The third challenging limitation is the fMRI image dependence on the acquisition methodology. The fMRI data is basically a statistical dataset defining the time courses of the appearance of the activity patterns. Several software tools are available like SPM, MRICRO, AFNI etc., which can transform the statistical data to make them appear as color blobs on the gray image of the brain. Each method is different from another and need extensive understanding of the tool to perform activity overlay. The activity maps for any predefined task are the same irrespective of the tools used. The motivation for research therefore is to find a method of considering only the activity maps and not the statistics.

The fMRI data is acquired through experimentation performed on nine different normal subjects performing different predefined tasks. We have considered three tasks: The motor task (Fig-1) involving movement of the left thumb.

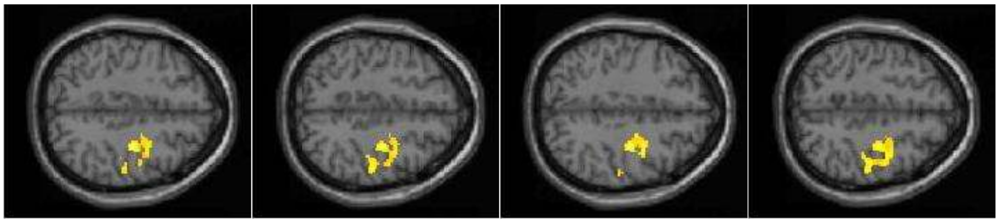


Fig-1: The axial slices of the brain with motor activity representation

The experimentation involves the movement of the left thumb during the active phase and no activity during the rest phase. The subject is cautioned about not touching the palm with the thumb which in any case would result in inclusion of touch activity to the intended thumb movement motor activity. The resulting images obtained with the aid of SPM show the activity maps on the prefrontal area of the right hemisphere of the brain. This specifically indicates the upper left limb motor activity.

The second experimentation involves vision task (Fig-2) where visualization of a checker board is considered. The subjects are made to view a checkerboard during the active phase and the checkerboard is removed during the rest phase. During the rest phase they view an empty white wall. Vision is bilateral and so the activity maps as rendered from SPM exist in the occipital region on either hemisphere of the brain.

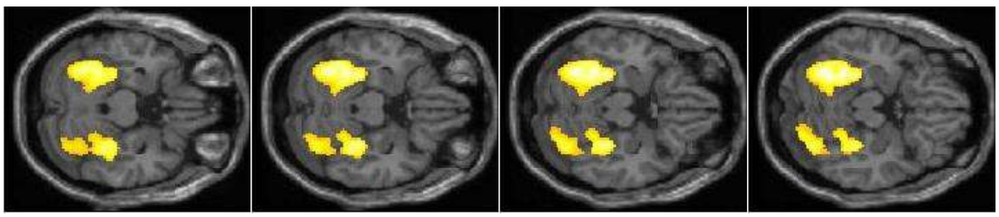


Fig-2: The axial slices of the brain with Vision activity representation

The third task considered for experimentation is the Visio-memory task (Fig-3) where visualization of scenes and memorizing the same is considered. In this case the subject is made to view certain predefined number of random scenes during the encode phase. During the retrieve phase the scenes are randomly mixed with some more scenes and are presented to the subject. The subject has to recognize the scenes shown during the encode phase. The results show activity in occipital region indicating the involvement of vision activity and also in the parietal region indicating the involvement of memory during retrieval phase.

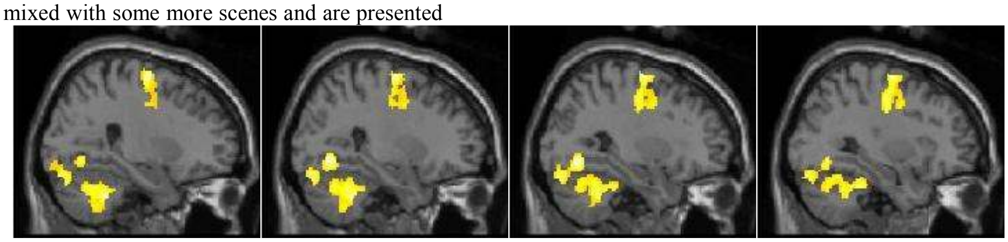


Fig-3: The Sagittal slices of the brain with visio-memory activity representation

It has become widely acknowledged that successful applications of neural computing require a principled, rather than unplanned, approach. The classification in our proposal is therefore based on back propagation neural networks which can effectively classify huge datasets and also consider data with unequal dimensions.

2. BACK PROPAGATION NEURAL NETWORK FOR CLASSIFICATION

The traditional fMRI classification methods are applied on individual subjects. It is observed that the activity patterns vary from person to person [3]. This characteristic of fMRI data instantiates the need for methods which consider groups of subjects rather than individual subject's data for classification. It would give a general perspective to the classification algorithm. This has motivated us to propose an approach to improve multiclass classification across groups of subjects. Spatially normalized activation maps of cluster of subjects are segmented into functional areas using a neuroanatomical atlas. Then each map is classified separately using local classifiers.

Standard back propagation is a gradient descent algorithm, similar to the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term *back propagation* refers to the manner in which the gradient is computed for nonlinear multilayer networks. Properly trained back propagation networks tend to give reasonable answers when presented with inputs that they have never trained with. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

The fMRI data set is huge and also the data size for different tasks is dimensionally dissimilar. The traditional back propagation algorithm is therefore aptly modified by presenting the dataset in the form of principal components.

The principal component analysis is a method used for dimensionality reduction and feature dataset
dimension mismatch [4]. Dimensionality reduction of high dimensional data is useful for three general reasons; it reduces computational requirements for subsequent operations on the data, eliminates redundancies in the data, and, in cases where

the feature data set dimensionality doesn't match then a common dimension is to be arrived at with the available data. All three reasons apply for the fMRI data representing the depth where it is found that the depth values vary considerably for three orientations (Table-1) (Axial, Sagittal and Coronal) of the brain images.
The total number of brain slices which have the activity patterns in them or the volume of brain involved in any activity is referred to as the depth feature. The depth information is represented in the form of brain slice numbers. The slice numbers are assigned with reference to the brain iso-center. The slices are acquired at an interval of 2mm depth.

	Axial		Sagittal		Coronal	
Sub 1	-34mm	8mm	-40mm	46mm	44mm	-100mm
Sub 2	-32mm	10mm	-42mm	48mm	42mm	-102mm
Sub 3	-34mm	8mm	-40mm	46mm	44mm	-98mm
Sub 4	-36mm	8mm	-46mm	46mm	40mm	-102mm
Sub 5	-32mm	8mm	-44mm	48mm	42mm	-102mm
Sub 6	-36mm	10mm	-44mm	48mm	34mm	-100mm
Sub 7	-34mm	12mm	-42mm	46mm	34mm	-100mm
Sub 8	-34mm	12mm	-42mm	46mm	44mm	-100mm
Sub 9	-32mm	8mm	-42mm	46mm	42mm	-102mm

Table-1: The raw fMRI data representing the depth information of the activity pattern in the brain images when imaged in three orientations

The depth values give the extent of existence of activity patterns in each direction. The axial slices involved in the activity in the typical case considered (from table-1) are found as 24 slices. The total numbers of slices of the brain that are responsible for the specified activity in the sagittal direction are 47 slices. The activity pattern when imaged in the coronal direction is found in 71 slices. The noticeable variations in the dimensions of the raw fMRI depth data motivates us to include the use of Principal Component Analysis (PCA), a standard method for creating uncorrelated variables from best-fitting linear combinations of the variables in the raw data (Table-2).

Motor-axial					Motor-Sagittal				Motor-coronal		
Subject1	0.8143	-0.571	0.1067		0.9995	-0.033	-4E-09		0.8849	0.4318	-0.174
Subject2	0.7288	0.6116	-0.308		0.9995	-0.033	-4E-09		-0.46	0.8644	0.2037
Subject3	0.74	0.5995	-0.305		0.9995	-0.033	-4E-09		0.8005	-0.202	0.5641
Subject4	0.8143	-0.571	0.1067		0.9995	-0.033	5E-09		0.8849	0.4318	-0.174
Subject5	0.3265	0.8015	0.5009		0.1329	0.9911	-8E-09		-0.46	0.8644	0.2037
Subject6	0.7288	0.6116	-0.308		0.033	0.9995	-3E-09		0.8005	-0.202	0.5641
Subject7	0.8143	-0.571	0.1067		0.9995	-0.033	-1E-09		-0.46	0.8644	0.2037
Subject8	0.3265	0.8015	0.5009		0.033	0.9995	1E-08		0.8849	0.4318	-0.174
Subject9	0.8143	-0.571	0.1067		0.9995	-0.033	9E-09		0.8925	0.4143	-0.178
Vision-Axial					**Vision-Sagittal**				**Vision-Coronal**		
Subject1	0.9829	0.0732	-0.138		0.9541	0.2759	0.1065		0.9933	-0.114	0.015
Subject2	0.9691	-0.238	0.0588		0.9541	0.2759	0.1065		0.9933	-0.114	0.015
Subject3	0.9701	0.1965	-0.051		0.9868	-0.06	-0.111		0.996	-0.087	0.0218
Subject4	0.9571	-0.284	0.0451		0.9749	-0.184	-0.009		0.996	-0.087	0.0218
Subject5	0.9824	-0.071	-0.042		0.9887	-0.047	-0.104		0.9902	0.0702	-0.121
Subject6	0.9713	0.2048	-0.028		0.9783	-0.168	-0.005		0.996	-0.087	0.0218
Subject7	0.9829	0.0732	-0.138		0.9851	0.0866	-0.09		0.9902	0.0702	-0.121
Subject8	0.9691	-0.238	0.0588		0.9843	0.0792	-0.098		0.9815	0.1768	0.0737
Subject9	0.9189	0.2918	0.2525		0.9327	-0.257	0.2222		0.9815	0.1768	0.0737
Visio-memory-Axial					**Visio-memory-Sagittal**				**Visio-memory-Coronal**		
Subject1	0.9965	-0.058	-0.058		0.9833	-0.14	-0.047		0.9623	0.2235	0.1159
Subject2	0.9925	-0.097	-0.073		0.9831	-0.136	-0.053		0.9796	-0.052	-0.15
Subject3	0.9965	-0.058	-0.058		0.9791	-0.032	-0.156		0.9605	0.0553	0.2711
Subject4	0.9949	0.0507	-0.027		0.9765	-0.021	-0.173		0.9767	-0.214	0.0161
Subject5	0.9884	-0.129	0.0799		0.9604	-0.194	0.1386		0.9767	-0.214	0.0161
Subject6	0.9898	0.1402	0.0194		0.8683	0.4925	0.057		0.9767	-0.214	0.0161
Subject7	0.9898	0.1402	0.0194		0.8683	0.4925	0.057		0.9846	0.1384	-0.092
Subject8	0.9898	0.1402	0.0194		0.929	-0.228	0.2591		0.9846	0.1384	-0.092
Subject9	0.9884	-0.129	0.0799		0.9831	-0.136	-0.053		0.9846	0.1384	-0.092

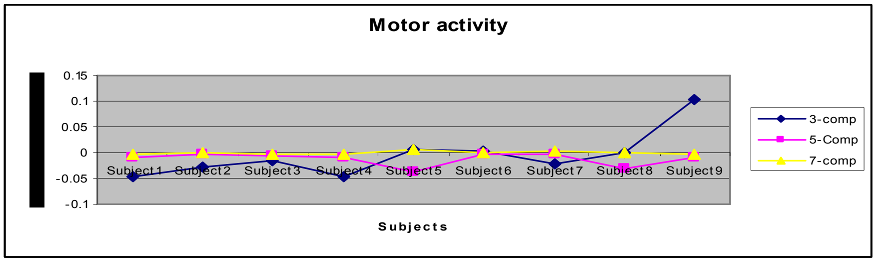
Table-2: The 3 principal components representing the fMRI data set of the brain imaged in all three orientations

1.1 Performance Evaluation with multiple component consideration

The decision on the number of components is heuristic. The graph (Fig-4) shows the classification errors while

incorporating three, five and seven principal components for classification.
The graph indicates that the classification error is less for five components as compared to three components. The change in error values for five and seven components is very minimal. We therefore fix the number of principal components to seven for creating the template for recognition/classification.

The back propagation neural network is a multilayer network that comprises of input, hidden and output layers [5][6]. The number of nodes in the input layer is equal to the number of features used for class representation. The number of nodes in the output layer is equal to the number of classes needed. The number of nodes in the hidden layer mainly decides the refinement to the inputs such that the output goal is reached in shortest duration of training period.



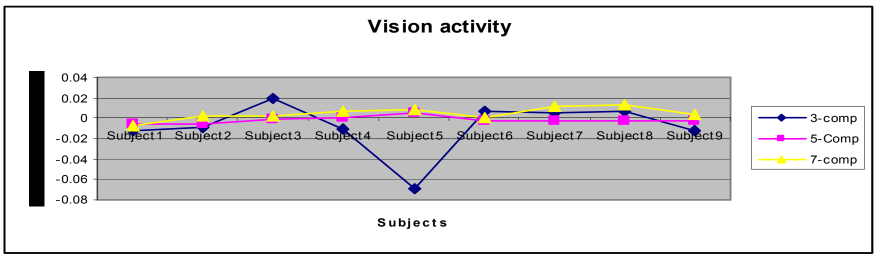


Fig-4: Graphical representation of classification error for 3, 5 and 7 principal components.

We therefore verify the time lapsed in training session for multiple number of hidden layer nodes for the outputs to reach a value that is nearest to the predefined target output by a factor of 0.1. The results indicate that (Table -4 (a), (b)) ((Fig-5) (Fig-6)) the performance goal is reached when the number of hidden layer nodes is 25 and the number of epochs is 4500 in the shortest duration of time. Decrease `in the value of both hidden layer nodes and epochs results in under training and more number in over training.

Table–4: (a) The Performance goal values for different number of hidden layer nodes and (b) The Training time Periods for different epochs and number of hidden layers

Hidden layer nodes	10	15	20	25	30	35
Epochs	Performance					
500	0.53	0.42	0.34	0.35	0.36	0.27
1000	0.36	0.35	0.29	0.31	0.48	0.22
1500	0.32	0.34	0.28	0.29	0.41	0.51
2000	0.22	0.22	0.25	0.25	0.53	0.31
2500	0.21	0.2	0.24	0.16	0.23	0.31
3000	0.16	0.19	0.22	0.12	0.2	0.25
3500	0.12	0.15	0.13	0.15	0.18	0.19
4000	0.16	0.14	0.15	0.13	0.17	0.14
4500	0.15	0.14	0.17	0.099	0.11	0.16
5000	0.13	0.11	0.099	0.099	0.099	0.11
5500	0.11	0.099	0.099	0.099	0.099	0.099
6000	0.099	0.099	0.099	0.099	0.099	0.099

Hidden layer nodes	10	15	20	25	30	35
Epochs	Training Time Elapsed (Secs)					
500	1.22	1.43	1.3	1.3	1.3	1.5
1000	2.39	2.4	2.4	2.6	2.54	2.65
1500	3.6	3.57	3.6	3.6	3.9	3.9
2000	4.75	4.73	4.7	5	5.06	5.4
2500	5.9	6.25	6.05	6.3	6.4	6.7
3000	6.9	7.5	7.6	7.9	7.7	8.01
3500	8.5	8.2	9.03	9.3	9.7	9.2
4000	9.48	9.2	6.4	10.35	10.2	10.48
4500	10.9	11.2	11.6	10.42	11.7	11.8
5000	10.62	12.5	12.3	12.12	12.5	13.4
5500	12.2	13.7	12.7	13.87	13.7	14.12
6000	13.5	14.6	13.64	14.5	14.8	14.5

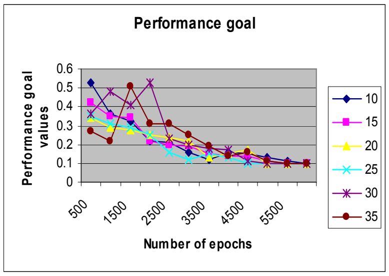


Fig-5:The training Performance graph

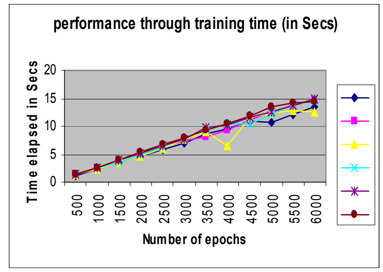


Fig-6: The training time lapse graph

1.2 Classification efficiency evaluation

The traditional method of leaving-one-out technique is used for performance evaluation of training methodology. In this method, one of the available samples is excluded, the classifier is designed with the remaining samples, and then the classifier is applied to the excluded sample [7]. This procedure is repeated with each available sample: if N training samples are available, N classifiers are designed and tested. The training and test sets for any one classifier so designed and tested are independent. This method is mainly effective in case of unavailability of large dataset for training which is true in the case of fMRI dataset. The classification efficiency is then checked by plotting the results on the Receiver Operating Characteristics (ROC) [8].

Table-6: The classification efficiency indicative values

A	B	C
TPR = 0.953	TPR = 0.906	TPR = 0.937
FPR = 0.063	FPR = 0.1875	FPR = 0.078
ACC = 0.95	ACC = 0.86	ACC = 0.93

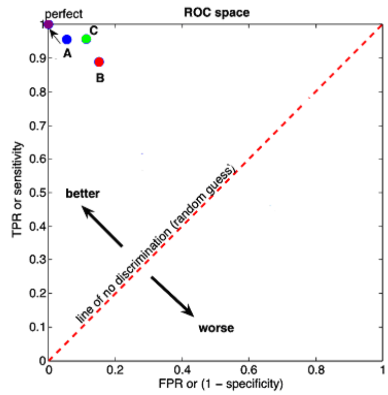


Fig-7: The ROC space indicating the classification efficiency

The classification efficiency with Back propagation algorithm where the features are represented with principal components is exceptionally good. This justifies the use of principal components for feature representation. But the fMRI data is more vulnerable to variations from subject to subject and stimulus to stimulus. The statistical methods have always proved effective while handling uncertain features sets. The classification is therefore checked with statistical method which is more appropriate in classification of traditionally fluctuating fMRI data.

2. STATISTICAL METHOD FOR CLASSIFICATION

Among the various frameworks in which pattern recognition has been traditionally formulated, the statistical approach with Bayesian probabilistic approach for classification has been most intensively studied and used in practice [9]. The Bayesian classification is based on the conditional dependency of the features of different classes. The fMRI dataset in three orientations are three independent identities which are not dependent on each other but the activity is seen as a combined effect of the three datasets.

The traditional method of Bayesian classification cannot therefore be considered for fMRI activity pattern classification. The conditionally independent characteristic of the naïve Bayesian classifier which is an improvised version of the Bayesian algorithm is suitably employed in this application. The probability of existence of activity in the image considered in all the three orientations of brain imaging is considered. The combined probability is obtained through naïve Bayesian approach for each type of task performed [10].

2.1 Naïve Bayesian approach

The Traditional statistical classification is based on the probabilistic approach. Abstractly, the probability model for a classifier is a conditional model,

$$P(C|F_1,\ldots\ldots,F_n)$$

over a dependent class variable C with a small number of outcomes or classes, conditional on several feature variables F1 through Fn. The problem is that if the number of features n is large or when a feature can take on a large number of values, then basing such a model on probability tables is infeasible. The model is therefore reformulated to make it more tractable.

Using Bayesian theorem,

$$P(C|F_1,\ldots\ldots,F_n) = \frac{p(C)\, p(F_1,\ldots\ldots,F_n|C)}{p(F_1,\ldots\ldots,F_n)}$$

In practice only the numerator of this fraction is of interest, since the denominator is independent of C and the values of the features Fi are given, so that the denominator is effectively constant. The numerator is equivalent to the joint probability model,

$P(C,F_1,\ldots\ldots,F_n)$ which can be rewritten as follows, using repeated applications of the definition of conditional probability:

$$P(C|F_1,\ldots,F_n) = p(C)p(F_1|C)p(F_2,\ldots\ldots,F_n|C,F_1)$$
$$= p(C)p(F_1|C)p(F_2|C,F_1)p(F_3,\ldots\ldots,F_n|C,F_1,F_2)$$
$$=p(C)p(F_1|C)p(F_2|C,F_1)p(F_3|C,F_1,F_2)p(F_4,\ldots\ldots,F_n|C,F_1,F_2,F_3)$$

and so forth.

The "naive" conditional independence assumptions are now considered: assume that each feature Fi is conditionally independent of every other feature Fj for **j ≠ i**. This means that $p(F_i|C,F_j) = p(F_i|C)$ and so the joint model can be expressed as,

$$p(C,F_1,\ldots\ldots,F_n)=p(C)p(F_1|C)p(F_2|C)p(F_3|C)\ldots\ldots = p(C) \prod\nolimits^{n}_{i=1} p(F_i/C)$$

This means that under the above independence assumptions, the conditional distribution over the class variable C can be expressed as:

$$p(C,F_1,\ldots\ldots,F_n) = \frac{1}{Z}\, p(C) \prod\nolimits^{n}_{i=1} p(F_i/C)$$

where Z is a scaling factor dependent only on $F_i1,\ldots\ldots F_in$, i.e., a constant if the values of the feature variables are known.

In our application the three classes considered represent three separate activities. The probability of each class is assumed to be the same and therefore.

$$P(V) = P(M) = P(VM) = 0.33$$

Where, P(V), P(M) and P(VM) represent the probabilities of vision, motor and visio-memory activities respectively.

The conditional probabilities of each class for features extracted in Axial direction [P(A/V), P(A/M), P(A/VM)], Sagittal direction [P(S/V),P(S/M),P(A/VM)] and Coronal direction [P(C/V), P(C/M), P(C/VM) are considered along with the class probabilities to generate the individual probability values

The probability values form the basis for classification. A new pattern when presented will be classified based on the standard decision rules. The most common decision rule used in statistical models is the Maximum A Posteriori (MAP) rule.

2.2 The MAP rule for classification

To construct a classifier from the probability model we consider the probabilistic approach of classification which is derived from the independent feature model, that is, the naive Bayesian probability model. The naive Bayesian classifier combines this model with a decision rule. One common rule is to pick the hypothesis that is most probable; this is known as the MAP decision rule [26]. The corresponding classifier is the function classify defined as follows:

Classify $(f1,\ldots\ldots., fn) = \mathrm{argmax}_c\, P(C=c) \prod_{i=1}^{n} p(F_i = f_i)/C = c)$

The probability of the test pattern is calculated in the same manner as the calculations done for training patterns to compare with the probability values that are arrived at by the training patterns. The MAP decision rule is then applied to arrive at a conclusion about the pattern represented by the test pattern. The efficiency of the classifier is tested through leave-one-out technique. The leave-one-out technique provides the least-biased (practically unbiased) estimate of the classification accuracy of a given training set, and is useful when the number of samples available with known classification is small.

2.3 Classification efficiency evaluation

The classification efficiency of the classifier is evaluated using the leaving-one-out technique as discussed in the previous method and the results are checked (Table-8). The ROC curve (Fig-8) is indicative of the classification efficiency of the three classes. This mainly depends on where the intersecting point of sensitivity and specificity lies in the graph with reference to the line of discrimination.

Table-8: The classification efficiency indicative values

A	B	C
TP=60 FP=05 65 FN=04 TN=59 63 64 64 128	TP=48 FP=22 70 FN=16 TN=42 58 64 64 128	TP=58 FP=07 65 FN=06 TN=57 63 64 64 128
TPR = 0.938	TPR = 0.75	TPR = 0.91
FPR = 0.078	FPR = 0.34	FPR = 0.11
ACC = 0.92	ACC = 0.703	ACC = 0.898

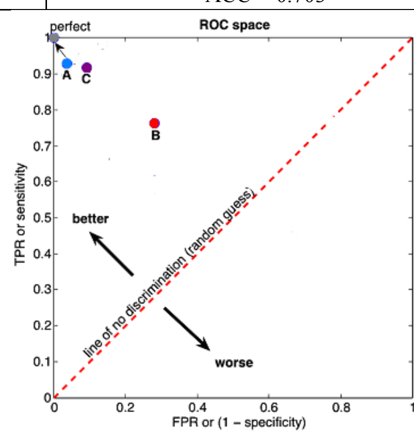


Fig-8: The ROC space indicating the classification efficiency

The efficiency table and the graph clearly represent the good efficiency in classification for motor task because it is a non bilateral task and there are very minimal possibilities of any interference from other regions in the brain. The visio-memory task involves both bilateral vision task and also the non bilateral memory task. A little decrease in efficiency may be accounted for the existence of the bilateral vision task which involves two prime activities but it is relatively compensated by the stable non bilateral memory task. The efficiency of the vision task has more deviations and is less efficient in few cases. This is mainly because vision task is bilateral and the chance of erroneous classification can be accounted for the existence of two prime activities.

3. RESULTS AND ANALYSIS

The classification is performed with two distinct methodologies. The methodologies are considered with reference to the prime characteristics of the fMRI data. The huge size of the fMRI data is taken into account in back propagation algorithm which is the most efficient of all the neural networks when huge data is to be classified. The fMRI data varies for the same subject and also for a repeated attempt of execution of same task. These variations prompt us to consider probabilistic approaches for classification. The Naïve Bayesian method caters to the conditionally independent characteristic of the fMRI data.

The results of classification are compared for the two methodologies. The efficiency values indicated by the ROC plot clearly indicate that the classification efficiency of the back propagation algorithm is better as compared to the naïve Bayesian technique. This is mainly because the data for back propagation network are the principal components which are known to represent any data in a very efficient way. The classification efficiency of the vision activity which is low as compared to the rest of the values is mainly because of its bilateral characteristic. This deficiency is also overcome in back propagation techniques because of the representation of the data through principal components.

4. CONCLUSION

An attempt is made towards implementation of a technique for classifying spatial patterns in brain activation maps. Our method consists of selecting appropriate activation maps obtained through SPM in all the three brain imaging orientations. Reduce the dimensionality of depth values using PCA, and creating a classifier using back propagation neural network and develop a training set of labeled activation maps. An attempt is made towards implementing different number of principal components. In accordance with the classification error that the network arrives at, an appropriate number of components is selected. The classification procedure is tested for three trained tasks and the classification with low error is achieved.

As fMRI data has a low signal to noise ratio, activation patterns may not be completely consistent even across the healthy control subjects. The statistical approaches thus are a better alternative in classification. Also the characteristics of the fMRI data are that the data representing the depth are not dependent on each other in the three orientations but each contributes significantly and substantially in a combined fashion for defining any activity. The decision on application of naïve Bayesian probability technique which emphasizes the conditionally independent characteristics of the features defined for a specific event turns out to be an obvious option. The statistical data forms the basis for applying the naïve Bayesian probability technique to generate the probabilistic values for all the three events under consideration. The MAP rule is applied to classify the test pattern into one of the three classes. The efficiency of the same is checked through leaving-one-out technique and has given effective results which justify the choice.

5. REFERENCES

1. Kenneth A. Norman, et, al, "Beyond mind-reading: multi-voxel pattern analysis of fMRI data", TRENDS in Cognitive Sciences, vol 500, 2006.
2. Heidi Johansen-Berg, et, al, "Correlation between motor improvements and altered fMRI activity after rehabilitative therapy", Brain, Vol 125, pp 2731-2742, 2002.
3. Helena Grip, et, al, "Classification of Neck Movement Patterns Related to Whiplash-Associated Disorders Using Neural Networks", IEEE Transactions on Information Technology in Biomedicine, vol. 7, no. 4, pp 412-418, December 2003.
4. H N Suma, S Murali “Principal component analysis for Analysis and Classification of fMRI Activation Maps”, International journal of computer science and network security, VOL 7, No 11, 235-242, Nov 2007.
5. Insung Jung, et, al, "Pattern Classification of Back-Propagation Algorithm Using Exclusive Connecting Network", International Journal of Computer Science and Engineering, Vol 2; pp 76-80,2008.
6. H N Suma, Murali S, “Neural network approach towards pattern classification using fMRI activity maps”, proceedings of IEEE indexed International Conference on computer communication Engineering-ICCCE08, pp 288-292, Kuala lampur, Malaysia, 2008.
7. Francisco Azuaje, "Genomic data sampling and its effect on classification performance assessment", BMC Bioinformatics, Vol 4:5, 2003.
8. Seong Ho Park, et, al, "Receiver Operating Characteristic (ROC) Curve: Practical Review for Radiologists", Korean Journal of Radiology, Vol 5, pp 11-18, 2004.
9. Saulius J. Garalevicius, "Memory–Prediction Framework for Pattern Recognition: Performance and Suitability of the Bayesian Model of Visual Cortex", American Association for Artificial Intelligence, 2007.
10. H N Suma, Murali S, “Naïve Bayesian classification approach towards classification of fMRI activity maps”, proceedings of International Conference on cognition and Recognition ICCR-08, pp 580-586, Mysore 2008.