# Object Categories Specific Brain Activity Classification with Simultaneous EEG-fMRI

Rana Fayyaz Ahmad, *Member, IEEE*, Aamir Saeed Malik, *Senior Member, IEEE*, Nidal Kamel, *Senior Member, IEEE* and Faruque Reza

*Abstract*— **Any kind of visual information is encoded in terms of patterns of neural activity occurring inside the brain. Decoding neural patterns or its classification is a challenging task. Functional magnetic resonance imaging (fMRI) and Electroencephalography (EEG) are non-invasive neuroimaging modalities to capture the brain activity pattern in term of images and electric potential respectively. To get higher spatiotemporal resolution of human brain from these two complementary neuroimaging modalities, simultaneous EEG-fMRI can be helpful. In this paper, we proposed a framework for classifying the brain activity patterns with simultaneous EEG-fMRI. We have acquired five human participants' data with simultaneous EEG-fMRI by showing different object categories. Further, combined analysis of EEG and fMRI data was carried out. Extracted information through combine analysis is passed to support vector machine (SVM) classifier for classification purpose. We have achieved better classification accuracy using simultaneous EEG-fMRI i.e., 81.8% as compared to fMRI data standalone. This shows that multimodal neuroimaging can improve the classification accuracy of brain activity patterns as compared to individual modalities reported in literature.**

## I. Introduction

Human brain has complex dynamics and it produces brain activity patterns carrying encoded information. Non-invasive measurement of human brain activity can give suitable extent of information to decode the different mental states. Brain activity analysis can able to tell us about what a person is seeing, perceiving or remembering. Brain reading or mind reading is today hot topic of research and debate [1]. Human visual imagery defined as seeing with mind's eye. When person is creating a visual image of orange, the required information to construct an orange is available mentally as the person in actual perceiving it [2]. The main question arises that could it be possible to decode human vision or visual system and how the information is encoded and decoded. Haxbey and colleagues [3] had used functional magnetic resonance imaging (fMRI) to measure the different patterns of blood oxygen level dependent (BOLD) activity occurring inside human brain in response to different objects in the ventral temporal cortex. Their result showed that if brain activity patterns were compared, high level object areas can able to predict what the participants were seeing i.e., the pictures of houses, faces, chairs, cats, bottles shoes etc. For each stimulus category, a distinct pattern was achieved. However, results showed for faces and object categories, ventral temporal cortex were widely distributed and also overlapping [3]. Cox & Savoy [4] used more advance algorithm for pattern classification to improve the prediction and classification results. In their study, multivariate statistical pattern recognition method was used to classify the fMRI based brain activity patterns evoked by the visual stimuli of various object categories. Results shown higher classification accuracy as compared to the traditional univariate analysis of fMRI data [4]. The similarity relationship between object responses is different in early visual area and high level object visual area. The activity patterns for both are quite different and were reported in literature [5]. In contrast to fMRI studies, EEG based approaches to classify/decode object categories and cognitive states were also done. Rousselet and colleagues [6] studied single trial EEG dynamics provoked by showing stimuli of noise textures, faces and houses. The response to each category is different in amplitude of EEG signals between the frequency range of 5-15 Hz. Stronger response to faces was observed as compared to textures and houses. In recent study, Sarabi and colleagues [1] decoded the basic object categories using task oriented EEG signals and employing wavelet transform with support vector machines. The classification/decoding capability of the EEG based study were not so much promising as compared to fMRI. However, fMRI cannot also give 100% accuracy. There is need to combine complementary nature of these two neuroimaging modalities together to achieve higher spatiotemporal resolution of human brain for better classification purpose.

Multimodal neuroimaging methods can be useful for better understanding of the brain dynamics. In the last decade, there has been growing interest to find the relationship between the electrophysiological and hemodynamics measurements of the brain activity i.e., EEG and BOLD fMRI. EEG signals recorded at scalp have high temporal resolution and poor spatial resolution due to limited number of electrodes. On the other hand, fMRI has very high spatial resolution and low temporal resolution. The complementary nature of EEG and fMRI can be combined to get high temporal and spatial resolution at the same time [7, 8]. However, simultaneous EEG-fMRI brings many technical

*This research work is supported by HiCoE grant (0153CA-005), Ministry of Education (MOE), Malaysia.

R.F. Ahmad is PhD Student from Centre for Intelligent Signal and Imaging Research (CISIR), Department of Electrical and Electronic Engg, University Teknologi Petronas, 31750 Tronoh , Malaysia (e-mail: rafayyaz@ gmail.com).

*A.S. Malik and N. Kamel are associate professors from Centre for Intelligent Signal and Imaging Research (CISIR), Department of Electrical and Electronic Engg, Universiti Teknologi Petronas, 31750 Tronoh , Malaysia (e-mail: *aamir_saeed@petronas.com.my).

F. Reza is with the Department of Neurosciene, University Sains Malaysisa, 16150 Kota Bharu, Malaysia.

challenges in terms of data acquisition and data analysis point of view [8, 9] . In this paper, we have proposed simultaneous EEG-fMRI approach to classify the object categories specific brain activity. This is the main novelty of our research work. We have acquired simultaneous EEG-fMRI data on human participants with 128 channel MR compatible EEG equipment and 3 Tesla Philips MRI scanners. We presented different object categories to the participants. Simultaneous EEG-fMRI able to capture the correlations between BOLD signal and EEG modulations which identified the task or object categories specific brain activities in terms of well localized activated volumes. Results have shown better classification accuracy with combine analysis of EEG and fMRI data as compared to fMRI data standalone. By enhancing the data analysis methods for combine EEG and fMRI data, the accuracy can further be improved. This can help researchers to understand the neural patterns of brain in a better way. Section II explains the data acquisition and experimental paradigms used for acquiring data. In section III, we described the complete methodology for simultaneous EEG-fMRI. Section IV shows the results acquired and section V ends with conclusion.

## II. Data Acquisition

### A. Subjects

Data were collected from five healthy right handed participants (University graduate students with normal vision or corrected to normal vision, mean age 25.5). All subjects have not any history of neurological or psychiatric disorders. Each participant signed consent form for their participation in this study. Also the study has been approved by human ethics committee of Universiti Sains Malaysia, Kota bharu, Malaysia.

### B. Experimental Paradigm

Experimental design for simultaneous EEG-fMRI is complex in nature. The main important concern is the efficiency of post experiment statistical analysis which relies on the experimental paradigm. Hence, it is mandatory to consider all the parameters before designing any experimental paradigm.

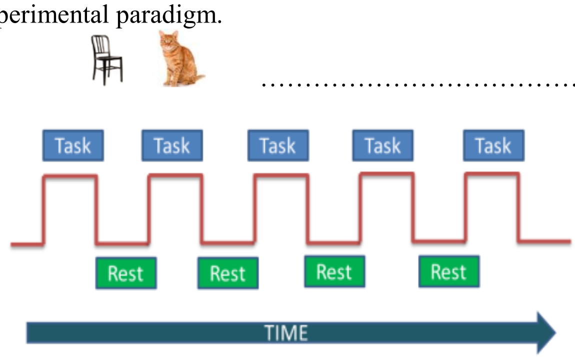


Figure 1. Experimental paradigm for Object categories

In our case, object categories were shown to participants. Each category picture (visual stimulus) is displayed for 2 seconds, after that there was inter stimulus interval (ISI) for 4 seconds and after that again different picture of same category has been shown to the participants and object categories were shown in random fashion. Figure 1 shows the experimental paradigm for object categories.

### C. Simultaneous EEG-fMRI data acquisition

Many technical challenges are involved to combine the EEG and fMRI neuroimaging modalities together. To develop simultaneous EEG-fMRI setup, the first thing required is to have MR compatible EEG equipment. Normal EEG equipment cannot be used inside the MRI scanner as due to the higher magnetic fields i.e., 3 Tesla or 7 Tesla. Figure 2 shows our developed data acquisition setup and data recording.

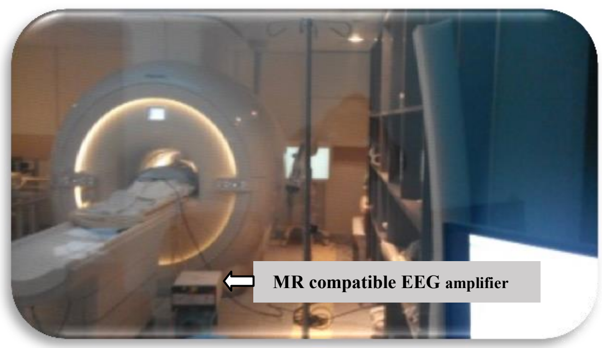


Figure 2. Data acquisition inside MRI scanner

### D. EEG Data Acquisition

EEG data has been acquired with 128 Channels MR compatible EEG equipment (EGI Systems, USA). The sampling rate is to be set 250 Hz which covers all desired frequency bands required for EEG data.

### E. fMRI Data Acquisition.

fMRI images were acquired with 3T Philips MR scanner. Gradient Echo Planner Imaging (EPI) was used on 3 Tesla Philips MRI scanner as pulse sequence with 2 second long repetition time (TR) and 35 milliseconds as echo time (TE). The matrix size of 64x64 was selected. The slice thickness was 3 mm with no slice gap. Whole brain anatomical scans were also acquired using T1-weighted sequence. The visual stimulus is shown through projector and participant was able to see it through reflecting mirror placed on his/her head.

## III. Method

Simultaneous EEG-fMRI data analysis is challenging to get brain activity patterns for classification purpose. It first involves the EEG and fMRI data processing to remove any kind of artifacts and ambiguities. After cleaning the data, the combine analysis method will be applied.

### A. EEG and fMRI Data preprocessing

EEG data acquired inside MRI scanner is highly contaminated with artifacts. Gradient artifacts (GA) due to magnetic fields present in the EEG data and these have large repetitive magnitudes. GA artifacts can be removed with template based method by subtracting the mean artifact from all the EEG data. Ballistocardiogram (BCG) artifacts induced in EEG data due to cardiac related activities and pulsatile blood flow. BCG artifacts are difficult to remove as compared to GA artifacts. Optimal basis set (OBS) is the commonly used method to remove these artifacts [10]. The first step for analyzing fMRI data is to preprocess it which includes slice time correction, re-alignment, co registration, normalization and spatial smoothing. The quality of the final results depends upon the preprocessing block. To get the better results, preprocessing should be done carefully [11].

### B. *Joint EEG-fMRI Analysis*

Different approaches are reported in literature for joint analysis of EEG-fMRI data. We have selected EEG informed fMRI analysis as asymmetric approach for combined analysis of simultaneous EEG-fMRI data.

#### 1) ***EEG informed fMRI Analysis***

In the EEG informed fMRI analysis approach, the main goal is to extract the EEG signal information along the experiment time course. The underlying neural activity recorded with EEG is directly related with the fMRI signals with respect to the external stimuli or events. Therefore, the EEG signal is convolved with the hemodynamic response function (HRF) and the result from this convolution is used as regressors in the fMRI analysis which uses a general linear model (GLM) [11]. The proposed methodology is shown in Figure 3.

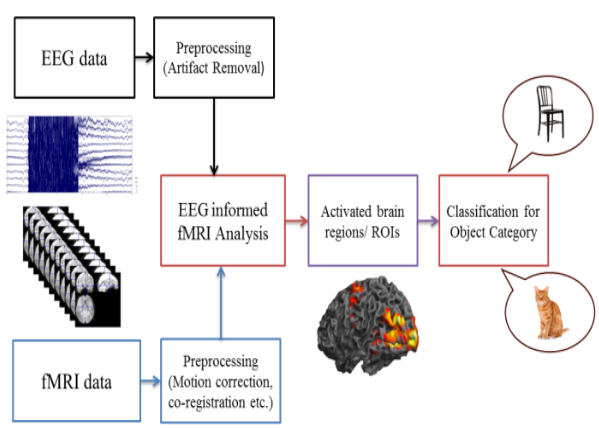


Figure 3. Proposed methodology for brain activity patterns classification

2) ***Classification:*** Support Vector Machines (SVM). Different machine learning techniques were employed to classify brain signals and reported in literature [12, 13]. However, one of the most used machine learning methods for classification of fMRI data is Support Vector Machines (SVM). SVM classifier is kernel-based approach to find functions of the input data that enable both classification and regression [14]. SVMs are considered the best state of the art classifiers having lower complexity as compared to other classifiers like neural networks, naïve Bayes and Fuzzy classifiers. SVM based upon a concept to find the hyper plane which can able to classify the data to the separate classes with possibility of maximum margin. For classifying different brain activity patterns, we selected the SVM classifier for classification purposes.

## IV. RESULTS

First EEG data has been passed from 0.3 Hz high pass filter and 50 Hz notch filter to remove DC component and power line noise respectively. Then EEG signal is band limited to 40 Hz with low pass filter because above this frequency MR related artifacts becomes more difficult to remove. EEG data was cleaned from GA and BCG artifacts with methods described in section 3.1. Also eye blinking and movement artifacts have been removed. Figure 4 shows the EEG data with gradient and BCG artifacts. Figure 5 shows clean EEG data in comparison to contaminated data for single channel.

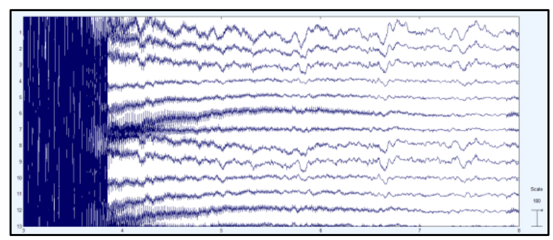

Figure 4. EEG data with gradient and BCG artifacts

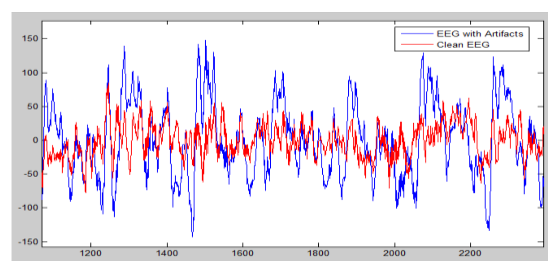


Figure 5. Clean EEG and EEG with artifacts-Single channel

For EEG-fMRI combine analysis, first clean EEG data were decomposed into time-frequency domain and we selected only occipital region electrodes as it is involved in visual related activity. Regressors were estimated using wavelet decomposition and these regressors were convolved with hemodynamics response functions (HRF) and fed into general linear model (GLM) using SPM8 for further fMRI analysis.

TABLE I. CLASSIFICATION ACCURACY RESULTS

| **Participant No.** | **fMRI** | **Simultaneous EEG-fMRI** |
|---|---|---|
| Participant 1 | 72% | 79% |
| Participant 2 | 78% | 81% |
| Participant 3 | 75% | 80% |
| Participant 4 | 79% | 83% |
| Participant 5 | 80% | 86% |
| Mean Accuracy | 76.8% | **81.8%** |

Thus, Brain activation maps for each participant were generated. Figure 3 also shows the brain activated regions in 3D brain. The voxels for region of interests (ROIs) were extracted from a sphere of radius 3 mm having centered on specific peak activity of the relevant contrasts. For each ROI, the subject specific peak was marked by visual inspection. After extracting the ROIs, they are passed into SVM classifier for classification purposes for each participant. Linear SVM kernel has been used. We have achieved 81.8 % classification accuracy between two object categories shown to the participants i.e., animals and human made objects like chairs. Also classification results were obtained using single neuroimaging modality i.e., fMRI and fMRI analysis was done with SPM8 [15] software and same classification process has been repeated as done for EEG-fMRI data. Classification accuracy results based on fMRI data were compared with simultaneous EEG-fMRI data results and are depicted in table I. Mean classification accuracy of 81.8 % has been achieved with simultaneous EEG-fMRI approach as compared to 76.8 % classification accuracy with fMRI data only. It shows that higher classification accuracy can be achieved with multimodal neuroimaging techniques i.e., simultaneous EEG-fMRI.

## V. Discussion

Object classification through brain activity patterns acquired with different neuroimaging modalities is an interesting topic of research in neuroscience community [1]. Many studies were conducted by researchers to classify the brain activity patterns using EEG, PET and fMRI etc. Each neuroimaging modality has some limitation in term of temporal and spatial resolution to capture enriched encoded information from the human brain. Simultaneous EEG-fMRI has proven a useful method to capture brain encoded information with higher spatiotemporal resolution. In this paper, we have proposed simultaneous EEG-fMRI method which can classify the brain activity patterns with better classification accuracy as compared to the individual modality standalone. We have acquired simultaneous EEG-fMRI data by showing object categories to the participants. EEG informed fMRI method for joint analysis was used to get the brain activity patterns with higher spatiotemporal resolution. These brain activity patterns associated to the object categories were extracted and then passed to SVM classifier for classification purposes to classify between the two object categories. Results have shown that 81.8% classification accuracy with SVM classifier has been achieved using simultaneous EEG-fMRI data as compared to 76.6% classification accuracy with fMRI data only. In addition, EEG based classification results are poor as compared to fMRI data. In future, others methods for simultaneous EEG-fMRI joint analysis can be applied and it can further improve the classification results.

## References


[1] M. Taghizadeh-Sarabi, M. R. Daliri, and K. S. Niksirat, "Decoding Objects of Basic Categories from Electroencephalographic Signals Using Wavelet Transform and Support Vector Machines," *Brain Topography,* pp. 1-14, 2014.

[2] K. P. Miyapuram, W. Schultz, and P. N. Tobler, "Predicting the imagined contents using brain activation," in *Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 2013 Fourth National Conference on*, 2013, pp. 1-3.

[3] J. V. Haxby, M. I. Gobbini, M. L. Furey, A. Ishai, J. L. Schouten, and P. Pietrini, "Distributed and overlapping representations of faces and objects in ventral temporal cortex," *Science,* vol. 293, pp. 2425-2430, 2001.

[4] D. D. Cox and R. L. Savoy, "Functional magnetic resonance imaging (fMRI)“brain reading”: detecting and classifying distributed patterns of fMRI activity in human visual cortex," *NeuroImage,* vol. 19, pp. 261-270, 2003.

[5] S. Nishimoto, An T. Vu, T. Naselaris, Y. Benjamini, B. Yu, and Jack L. Gallant, "Reconstructing Visual Experiences from Brain Activity Evoked by Natural Movies," *Current Biology,* vol. 21, pp. 1641-1646, 2011.

[6] G. A. Rousselet, J. S. Husk, P. J. Bennett, and A. B. Sekuler, "Single-trial EEG dynamics of object and face visual processing," *NeuroImage,* vol. 36, pp. 843-862, 2007.

[7] J. Jorge, W. van der Zwaag, and P. Figueiredo, "EEG–fMRI integration for the study of human brain function," *NeuroImage,* 2013.

[8] R. F. Ahmad, A. S. Malik, N. Kamel, F. Reza, and A. H. A. Karim, "Simultaneous EEG-fMRI data acquisition during cognitive task," in *Intelligent and Advanced Systems (ICIAS), 2014 5th International Conference on*, 2014, pp. 1-4.

[9] T. Ihalainen, L. Kuusela, S. Turunen, S. Heikkinen, S. Savolainen, and O. Sipilä, "Data quality in fMRI and simultaneous EEG–fMRI," *Magnetic Resonance Materials in Physics, Biology and Medicine,* pp. 1-9, 2014/04/26 2014.

[10] R. K. Niazy, C. F. Beckmann, G. D. Iannetti, J. M. Brady, and S. M. Smith, "Removal of FMRI environment artifacts from EEG data using optimal basis sets," *NeuroImage,* vol. 28, pp. 720-737, 2005.

[11] M. A. Lindquist, "The Statistical Analysis of fMRI Data," *Statistical Science,* vol. 23, pp. 439-464, 2008.

[12] F. Pereira, T. Mitchell, and M. Botvinick, "Machine learning classifiers and fMRI: a tutorial overview," *Neuroimage,* vol. 45, pp. S199-S209, 2009.

[13] H. U. Amin, A. S. Malik, R. F. Ahmad, N. Badruddin, N. Kamel, M. Hussain*, et al.*, "Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques," *Australasian Physical & Engineering Sciences in Medicine,* pp. 1-11, 2015.

[14] V. Vapnik and O. Chapelle, "Bounds on error expectation for support vector machines," *Neural computation,* vol. 12, pp. 2013-2036, 2000.

[15] (Accessed on 30 April , 2014). http://www.fil.ion.ucl.ac.uk/spm8.