Optimization and Development of Concurrent EEG-fMRI Data Acquisition Setup for Understanding Neural Mechanisms of Brain

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Abstract— **Electroencephalography (EEG) and functional magnetic resonance (fMRI) both are considered as non-invasive neuroimaging modalities. Both are used for understanding brain functionalities in cognitive neuroscience as well as in clinical applications. EEG gives high temporal resolution and it has poor spatial resolution. On the other hand, fMRI has very high spatial resolution and poor temporal resolution. For deep understanding of neural mechanisms inside human brain, it is desirable to get the higher spatiotemporal resolution of human brain at the same time. Concurrent EEG-fMRI data recording solve the problem of higher spatiotemporal resolution. It can be also helpful to understand the neural mechanism inside human brain effectively. The concurrent EEG-fMRI recording requires MRI compatible EEG equipment which can be placed inside the higher magnetic field of MRI scanner and also synchronization is required to make setup concurrent. To get higher signal to noise ratio (SNR), optimization of data acquisition parameters plays a significant role. In this paper, we discussed the some real issues during data acquisition and their optimization. We have developed the concurrent EEG-fMRI setup and also successfully recorded the EEG-fMRI data concurrently by optimizing the data acquisition parameters involved. Artifacts have been removed from the data and further, data fusion framework is proposed for combine analysis of EEG and fMRI data.**

Key words—**EEG, fMRI, Concurrent EEG-fMRI, BOLD**

I. INTRODUCTION

Different neuroimaging modalities are available to record the human brain activity for understanding neural mechanism of human brain in these days by the researchers and clinicians [1]. It is difficult to measure and localize the neural activity without placing the electrodes inside the human brain. Any neural activity inside the brain produces fluctuating electric and magnetic fields and it can be measured by placing electrodes on the scalp i.e., Electroencephalography (EEG). From the measured fields, it is difficult to estimate the all sources of neural activity. Electroencephalography (EEG) captures the neural activity from the scalp potentials [2] and on other hands magnetoencephalography (MEG) measures magnetic fields recorded through dense arrays of sensors [3]. The temporal resolution of EEG and MEG are very high in order of milliseconds [4]. These two neuroimaging modalities are capable to measure fast transitions or dynamics of neurophysiologic process. However, spatial resolution of EEG and MEG is poor. Functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) are functional neuroimaging modalities and both modalities measures the secondary effect instead of measuring the neural activity directly as compared to EEG and MEG [5]. Functional magnetic resonance imaging (fMRI) measures brain activation with high spatial resolution based on phenomena called blood oxygenation level dependent (BOLD).

EEG and fMRI are considered as complementary neuroimaging modalities in term of their resolutions. fMRI has very high spatial resolution measuring delayed response i.e., blood oxygenation level dependent (BOLD) signal after occurrence of any neural activity inside the brain [6]. On the other hand EEG has very high spatial resolution in milliseconds. To get high temporal and spatial resolution at the same time, concurrent EEG-fMRI data acquisition can be possible solution. Concurrent EEG-fMRI data recording give us the data with spatiotemporal resolution at the same time. This concurrent EEG-fMRI data can help researchers to understand neural mechanisms of human brain in better way.

In recent times, with the development of MRI compatible equipment which can tolerate and shield the higher magnetic field of MRI scanner, it becomes possible to acquire the EEG signals of human brain inside the fMRI scanner. This compatible equipment can produce good quality data output without affecting electrical signals due to higher magnetic fields and also addresses the safety requirement. Recently developed systems were based on 64 channel EEG equipment [7-11]. We developed concurrent EEG-fMRI setup using 128 channel EEG equipment which

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further improves the spatial resolution of EEG data as compared to other systems. This paper describes the development of concurrent EEG-fMRI data acquisition setup by incorporating the optimized parameters required for higher signal to noise ratio (SNR) and higher data quality based on the literature review. Further, we discussed different type of artifacts which were produced during the data acquisition process and remedy for their removal to achieve higher signal to noise ratio (SNR). Further, we have proposed data fusion approach for clean EEG and fMRI data which is the major advantage of concurrent EEG-fMRI setup to capture the common neural activity with higher spatiotemporal resolution which is not possible with individual modality. Section II describes the problem formulation and Section III give detail about concurrent data acquisition setup. In section IV, optimization of data acquisition parameters based on literature were carried out. Section V presents results for acquired concurrent EEG-fMRI data and data fusion framework. Section VI ends with conclusion.

II. Problem Formulation

The major problem in integration of EEG and fMRI together is the higher magnetic fields of MRI scanner. Normally MRI scanners have magnetic field strength of 1.5, 3.0 and 7.0 Tesla. Normal EEG equipment cannot be placed inside the MRI scanners. Therefore, MRI compatible equipment and setup is mandatory. Also EEG signals are corrupted with the gradient artifacts (GA) due to MRI scanner magnetic fields and Ballistocardiogram (BCG) artifacts. Synchronization of EEG and fMRI to make setup concurrent is also challenging task which requires hardware and software addition to the data acquisition setup of each modality.

III. Concurrent Data Acquisition Setup

To solve the issues related to magnetic field, non-magnetic and shielded equipment were used inside higher magnetic field of fMRI scanner. For EEG data acquisition, 128 Channels EEG equipment was used with 3.0 Tesla Philips fMRI scanner. To make setup concurrent, additional hardware was developed and used to synchronize the two neuro imaging modalities i.e., EEG and fMRI. TTL clock triggers from MRI scanner were used to make the system concurrent and to acquire the data at the same time. These trigger was converted to serial by our customized hardware and it initiates the experiment so at same time both EEG and fMRI data acquisition starts.

Also fiber optic communication link was established between fMRI scanner and control room inside of normal copper cabling. The setup was developed at Hospital Universiti Sains Malaysia. Fig. 1 shows the detail of our developed concurrent EEG-fMRI setup. It also shows human subject with 128 channel EEG cap and in second step, the subject is laid down in supine position inside the MRI scanner for concurrent EEG-fMRI data recording.

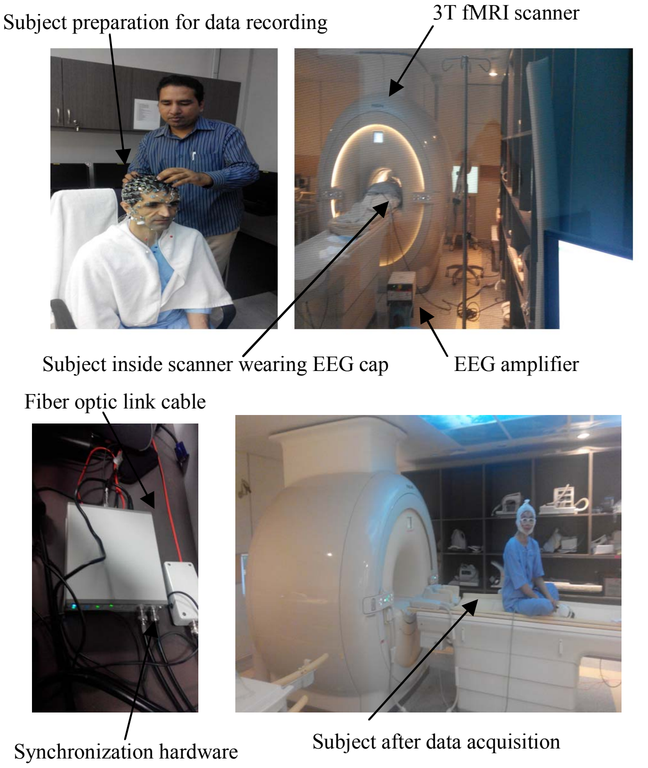

Fig. 1. Concurrent EEG-fMRI Data Acquisition Setup

IV. Optimization of Acquisition Parameter

Data acquisition parameters play an important role to get high quality data. EEG and fMRI both have their own parameters to be considered and optimized for better SNR for concurrent EEG-fMRI recording.

A. fMRI parameters selection

The selection and optimization of fMRI parameters has an impact on the combined EEG-fMRI data quality and it should be carefully selected based on the type of study. The most dominant fMRI parameters are: field strength, head coil, Echo time (TE), Repetition time (TR), Voxel dimensions, slice thickness and session length for experiment to be run [10]. Each parameter selection can affect the quality of data. For example, if static magnetic field (B_o) strength is higher, it directly affects the signal to noise ratio (SNR).Currently available choices are 1.5 Tesla, 3.0 Tesla and 7 Tesla MRI scanners. Therefore, 7T and 3T fMRI scanners produce high SNR in comparison to 1.5 T. For our concurrent EEG-fMRI study, we selected 3T Philips MRI scanner which can produce high SNR as compared to the 1.5T MRI scanners. Fig. 2 describes the SNR as a function of the voxel volume with different magnetic field strength. It is evident from this figure 7T MRI scanner has higher SNR with smaller voxel volume as compared to the 3T and 1.5 T [12]. Slice thickness defines the thickness of each brain slice image acquired during acquisition. Fig. 3

shows the slice thickness of brain i.e., thin and thick slices. If small slice thickness is selected, it increases the one scan time to cover full brain and it makes difficult to fully track the changes in BOLD signal. Hence for covering full brain 30 to 38 slices will be sufficient. Each slice thickness can vary between 3 and 4 mm. For our study, we selected slice thickness of 3.0 mm as optimized.

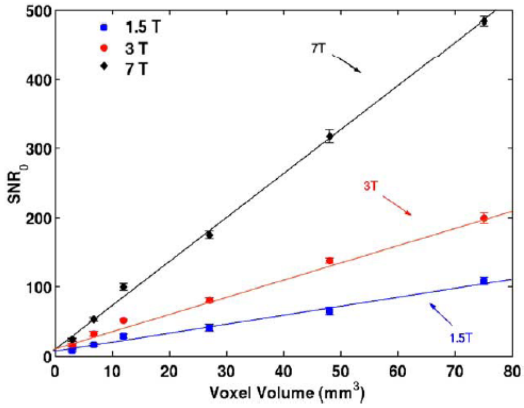

Fig. 2. SNR vs Field strength [12]

Repetition time (TR) affects the BOLD contrast to be captured by fMRI scanners. Selection of short TR will increase the sensitivity as compared to the long TRs i.e., greater than 4s. Fig. 4 clearly shows the different sensitivity results for long TR of 4 seconds and short TR of one second. It shows that short TR can capture more activation of the neuronal process inside the human brain as compared to long TRs.

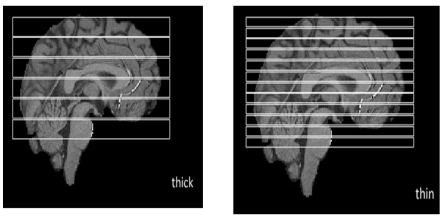

Fig. 3. Slice Thickness

Right selection of TR will produce better activation results. In our case, we selected duration of TR is 2 second which is optimal value for most of the experiments reported in literature. In contrast, long TRs will decrease the sensitivity of the neural activity to be captured by fMRI scanner.

TR=1s

TR=4s

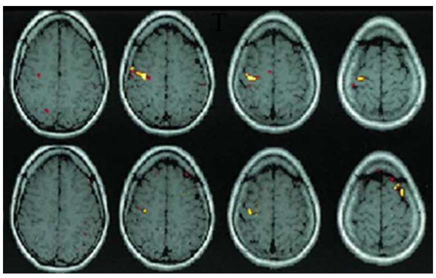

Fig. 4. Repetition Time (TR)

B. EEG parameter selection

For EEG data acquisition, the sampling rate plays a significant role to capture the electric potentials on the scalp. The frequency spectrum of EEG signal can be divided into different frequency bands i.e., delta (1-3 Hz), theta (4-7Hz), alpha (8-12 Hz), Beta (13-30 Hz) and gamma (31-50 Hz). By considering the maximum frequency present in the EEG signals, the sampling frequency of 250 samples/seconds is appropriate to cover all the frequency bands for analysis purposes. To increase the spatial resolution of EEG data, we selected 128 channel EEG caps. Most of previous concurrent EEG-fMRI studies were done with 19 channel and 64 channel EEG electrodes.

C. Optimized Data Acquisition Protocol

Based upon the parameters discussed in part A and B of this section, we have designed our data acquisition protocol which is optimized to get high signal to noise ratio. These optimized parameters for fMRI are given in Table I.

TABLE I. FMRI ACQUISITION PARAMETERS

Data Acquisition Parameters	Value
MRI Scanner	3.0 Tesla
Pulse Sequence	Gradient EPI
Repetition Time (TR)	2s
Echo Time (TE)	35ms
Image Matrix Size	64x64 pixels
Number of Slices	32
Voxel Size	3.x3x3 mm^3
Flip Angle	90^o
Field of View (FOV)	19.2cm
Data output format	DICOM

Table II shows the data acquisition parameters for EEG data recording.

TABLE II. EEG ACQUISITION PARAMETERS

Data Acquisition Parameters	Value
No of Electrodes	128
Sampling rate	250 samples/s
Reference	Average Reference

D. Choice of Experimental Paradigm

For studying neural mechanism and dynamics of brain, two types of experimental paradigms are followed i.e., block and event related design. Block design is based on similar trials to make a task specific condition e.g., active and rest. The major advantage of block design experiment is that higher signal to noise ratio is achieved after averaging many trials. Specific region of interest (ROI) for a specific task can be extracted using block designs [13].

Event related experiment design looks insight to extract information from neural activity from evoked hemodynamic responses. Event related designs are used to improve the temporal resolution of fMRI. The choice of any experimental paradigm is fully depends upon study under investigation.

For our data acquisition purpose, we selected and designed event related experiment. Visual stimulus has been shown to the participants i.e., different pictures of animals, humans and buildings etc. Each picture remains for 2 seconds and after that it disappears. Rest of time fixation cross was displayed for 5 seconds. Fig. 5 shows the experimental paradigm which evokes the neural activity inside the brain.

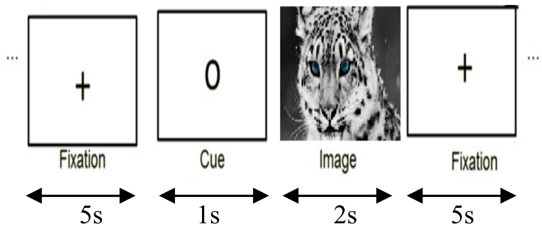

Fig. 5. Event Related Paradigm

E. Artifacts Removal

EEG data recorded during simultaneous EEG-fMRI experiment is contaminated with large repetitive artifacts which were induced due to the switching magnetic field gradients known as gradient artifacts (GA). GA artifacts are higher in magnitude as compared to the EEG signal's amplitudes which is in microvolts. Ballistocardiogram (BCG) artifacts are also present in the raw EEG signals. BCG artifacts are induced in EEG data due to cardiac-related activities, EEG electrode movement on scalp and conductive blood (due to ferromagnetic nature) in the static magnetic field of fMRI scanner. Fig. 6 shows acquired EEG data using our concurrent EEG-fMRI setup having gradient and Ballistocardiogram artifacts. The amplitudes of these induced artifacts are much larger than the normal EEG signals. Different methods have been reported in literature to remove gradient and BCG artifacts. Gradient artifacts (GA) have much larger amplitude than BCG artifacts and at first sight; it seems difficult to be removed. However, GA artifacts are much easier to remove as compared to BCG artifacts. The common method for GA removal is template based method. Allen's method for average wave form subtraction is commonly used to remove gradient artifacts [14]. BCG artifact is difficult to remove as its main source is from physiological activities inside the human body. Independent component analysis (ICA) can be used to decompose EEG data into many BCG activated components. However, removal of these components can be problematic if any neural activity related component mixed with BCG components is removed. Therefore, ICA based method for BCG removal is not much suitable. Optimal basis set (OBS) which is based on principal component analysis (PCA) is normally used to remove the BCG artifacts [15, 16].

V. Results

Based on our developed concurrent EEG-fMRI setup, EEG and fMRI data was recorded simultaneously to capture the common neural activity. In first step, EEG and fMRI data preprocessed separately to remove artifacts and in second step both preprocessed data merged together by applying data fusion method.

A. EEG Data Acquisition and processing

Fig. 6 shows the raw EEG signals acquired which were contaminated with artifacts like GA, BCG and eye blinks etc.

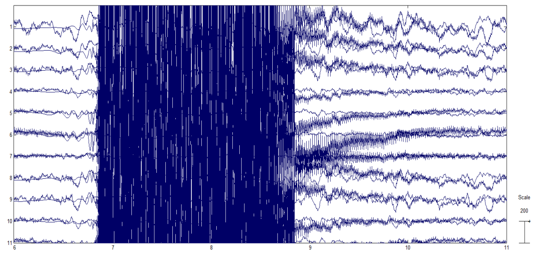

Fig. 6. EEG data acquired with gradient and BCG artifacts

Fig. 7 shows the clean EEG data after preprocessing i.e., band pass filtering (0.3-40 Hz) and also removing GA and BCG artifacts using OBS and AAS (Average artifact subtraction) methods.

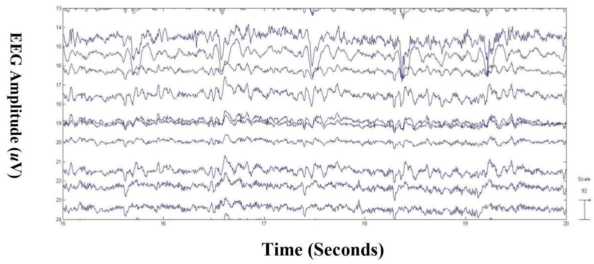

Fig. 7. Clean EEG Data

To give more clear view of artifact removal, Fig. 8 shows the power spectrum plot of contaminated EEG with the clean EEG after removing BCG as well as gradient artifacts. The clean EEG has less power magnitude as compared to the contaminated EEG with artifacts.

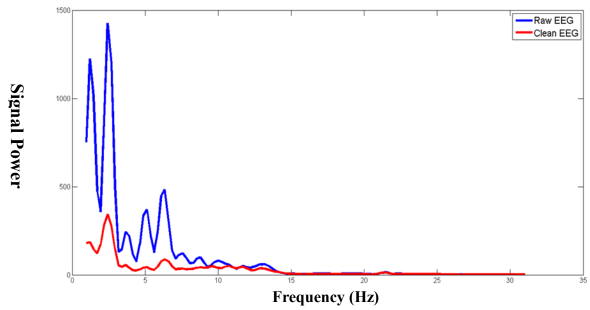

Fig. 8. Comparison of Power of Contaminated and Clean EEG Power spectrum

B. fMRI Data Acquisition and processing

Functional MRI data was acquired in DICOM format which was in terms of sequence of functional brain images. The first step after getting data is to analyze it using preprocessing pipeline which consist of slice time correction, motion correction, co-registration, normalization and spatial smoothing. The quality of the fMRI data dependent upon the pre-processing block. To get the better results, preprocessing should be done carefully [17].Fig. 9 shows the T1 weighted anatomical images of the human brain. It gives us the structural information of the brain which is used in during analysis for co registration and normalization purposes.

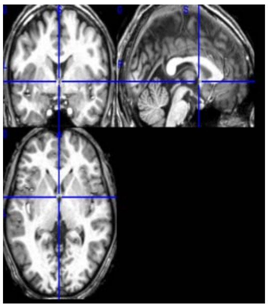

Fig. 9. Anatomical Images Acquired

Fig. 10 shows the functional MRI data. fMRI images has poor resolution as compared to anatomical MRI images as clear from the Fig. 9 and Fig. 10 comparison. These two kinds of images are further merged together in co-registration steps during preprocessing step.

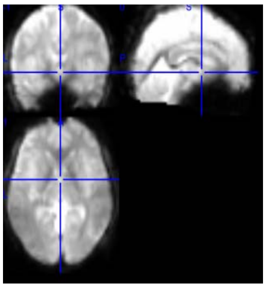

Fig. 10. Functional MRI Images acquired

C. Data Fusion

The main advantage of concurrent EEG-fMRI recording is that it can be used to fuse or combine the information acquired through EEG and fMRI. As the overall system is concurrent, so data fusion can be applied on the acquired EEG signals and fMRI images [1]. However, both modalities are at different space i.e., temporal and spatial domain. The common feature space is required for this purpose. EEG-fMRI fusion normally can be classified into two categories i.e., data driven and model driven approach. Model driven approach is difficult to implement as it is hard to predicate accurate biophysical model of human brain. Therefore, data driven i.e., blind source separation approaches are good for this purpose. It requires only EEG and fMRI data without forming any model. Independent component analysis (ICA) is a popular approach for joint analysis or fusion of EEG and fMRI. ICA able to identify the common sources from the linear mixture without having a prior knowledge of sources related to the neural activity [18]. ICA can able to estimate independent spatial ICA (sICA) or temporal ICA (tCA) components from EEG and fMRI data. However, physiological limitation recommends tICA for EEG data and sICA for fMRI data. Joint ICA (jICA) is a technique which is based on formation of generative model in joint framework of concatenated data of two modalities [19] i.e., in our case EEG and fMRI. jICA estimates components using Infomax theory. The fusion framework for EEG and fMRI is shown in Fig. 11. The clean EEG and fMRI data merged together to get the activation map of the common neural activity occurred inside human brain.

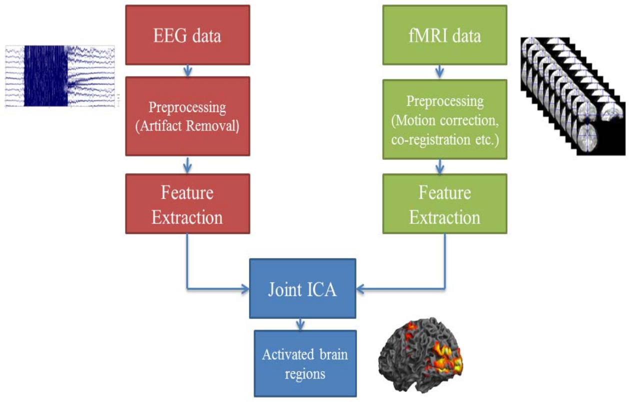

Fig. 11. EEG-fMRI Fusion framework based on Joint ICA (jICA)

VI. CONCLUSION

EEG and fMRI are widely used neuroimaging modalities for clinical applications. Each modality has some limitation in terms of resolution. To get high spatial and temporal resolution at the same time, the merger of two modalities solves this limitation. Concurrent EEG-fMRI data acquisition setup can provide better functional information to understand neural mechanism of human brain. To combine EEG and fMRI together, MRI compatible EEG equipment is required. Also optimization of data acquisition parameters is desirable to achieve higher signal to noise ratio (SNR) and better data quality. In this paper, we have developed the concurrent EEG-fMRI setup and optimized the parameters for both EEG and fMRI based on literature. EEG and fMRI data have been processed and results shows the clean data after removing different kind of artifacts. Further, we have proposed data fusion approach for combine analysis of EEG-fMRI data which can produce brain activation maps with higher spatiotemporal resolution using the EEG and fMRI clean data. This approach can help researchers and neuroscientist to better understand the neural mechanism of human brain by achieving higher spatiotemporal resolution at the same time which is not possible with individual modality.

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