EEG- fMRI Mapping and Techniques- A Review

K.ELAVARASI, P.RAJASEKAR

Abstract---- Multimodal Neuroimaging based diagnostic systems have recently gained attention in the diagnosis of brain disorders. fMRI and EEG has become commonly used non invasive technique for investigating various types of epileptic seizures with high spatial temporal resolution. This combined electrical and hemodynamic measurement of brain activity has more technical advantages and responds to epileptic discharges by improving the localization of epileptic foci. In this review various methods and the results of different epilepsy detection techniques have been discussed. As a conclusion that EEG-fMRI provides a multidimensional view that helps to localize epileptic foci with potential important implications to extend the scope of EEG/fMRI studies.

***Index Terms*— fMRI, Epilepsy, EEG, Haemodynamic, Multimodal Neuro imaging.**

I. INTRODUCTION

Brain is the most powerful and complicated organ in the body. To analyze the brain combined EEG and fMRI recording has been used to localize areas of increased blood flow that associated with specific EEG events. Integrating information of multimodal imaging that overcomes the limitations of single modality has become popular. Investigation of a large intersubject variability of EEG-fMRI correlation patterns using hierarchical clustering algorithm [1] local multimodal serial analysis an unsupervised method to compensate the deficiencies in integration and brain dysfunction[2] a review that examines the different modalities in neuroimaging for signal acquisition and monitoring the magnetic and electrical functionality of brain, various algorithms of feature extraction, conditioning steps that renders the electrical signals into control commands has been discussed[3] mapping of EEG signals obtained from the brain to a known combination of colours, in order to produce and project an image visualized in the mind and enhancing them[4] simultaneous recording of EEG and BOLD activity in patients with focal epilepsy, single event and average BOLD responses to EEG interictal epileptic discharges with focal epilepsy[5] integration of neuronal and hemodynamic processes during epileptic seizures in mesial temporal lobe epilepsies with partial emphasis on the neural and physiological correlates[6] comparison of different frequency dependent and independent transfer functions, experimental control over the frequency structure of the EEG signal by comparison of different and independent transfer functions, experimental control over the frequency structure of the EEG signal by entraining networks to visual simulation at different frequencies by simultaneously acquiring the signal from both modalities[7] demonstration of BOLD responses in partial epilepsy reflect both activations and deactivations mostly active spiking on routine scalp EEG recording[8] evaluation of source and extent of the brain structures involved in thalamus in generalized epileptic discharges and their evolution as the disease progresses[9] overview on the current study of epilepsy as well as human cognition and systems neuroscience and ongoing and anticipated methodologies[10] a non parametric approach to show that interictal discharges lead to blood oxygen level dependent response that is significantly different to that obtained by examining random events and optimization of analysis strategy[11] novel principal component analysis enhanced cosine radial basis function neural network classifier is used for accurate and robust classification of electroencephalogram into healthy,ictal and interictal EEGs[12] recovery of ultrahigh frequency EEG signatures, AAS requires invariantly sampled and imaging artifact waveforms to acheive optimal imaging artifact correction[13] a multidimensional view that contributes valuable clinical information to localize the epileptic focus with potential important implications for the surgical treatment of some patients with drug resistant epilepsy, and insights into the resting state and cognitive network dynamics[14] feature extraction technique followed by K-means clustering and principal component analysis as post classifiers for the classification of epilepsy risk levels[15] multiscale principal component analysis denoising method in terms of epileptic seizure detection also patient independent seizure detection algorithm using Freiburg database[16] computer aided diagnostic system to automatically identify the normal and abnormal activities using minimum number of highly discriminating features in classifiers and various challenges[17] provides additional evidence in support of intra and inter hemispheric transfer of language networks in patients with epilepsy using the more sensitive optimal time course method[18] estimation of seizure propagated pathway from fMRI data recorded by testing a set of clinically plausible network connectivity models of discharge propagation[19] novel automatic technique based on data mining for epileptic activity classification[20] dynamic principal component analysis approach and on partially extracted features, threshold of the pc classifier using the normalized partial energy sequence of the extracted features of the training data set[21] extreme learning machine based EEG classification approach is employed to train a single hidden layer feed forward neural network[22] review on certain soft computing techniques for pattern recognition such as neural networks fuzzy logic etc[23] a versatile signal processing and analysis of electroencephalogram for training and testing a seizure prediction method on data from individual petit mal epileptic patients[24] partial directed coherence analysis as a mechanism for feature extraction in the scalp EEG recordings for seizure detection [25] neural classifier for the recognition of mental tasks from online spontaneous EEG signals[26] feature selection and classification of the epileptic seizure by selecting the individual features[27] interpretation of chirp like striation patterns in processed spectrograms of single channel electrocortiograms

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associated with epileptic patients[28] empirical mode signal processing is employed for analyzing non linear and non stationary time series[29] SVM based automatic seizure detection which uses radial basis function for training data[30] higher order spectra analysis of pre-ictal and ictal epilepsy[31] sensitivity and specificity calculation of blood oxygen level dependent responses to interictal epileptic seizures[32] quantitative set of simulations with a realistic model of fMRI time series[33] multiple eigen time series in each ROI to avoid temporal information loss[34] challenges faced in eeg-fmri mapping [35] blind source separation and statistical model of EEG/fMRI and then exploit the learnt correlations to improve the results of signal processing[36] gamma HRF convolved time series of ictal events used as a regressor of intrest in the GLM analysis of the fMRI data[37] optimization of data acquisition parameters, concurrent and artifact removal[38] hieuristic analysis with spatio spectral EEG components where the filter response has two dimensions and depends on frequency and channels[39] classification accuracy of brain activity[40]Various filters and noise removal techniques in biomedical images[41]applying machine learning techniques in multimodal images like CT,MRI[42] For instance, the physiological data regarding patient can be supervised remotely by a doctor[43]. This paper is organized as general mapping modalities various methods, techniques and algorithm so far used in localization of epileptic seizures and artifact removal using EEG-fMRI mapping and the challenges and issues to be addressed in future in combining these modalities for epilepsy.

II EEG/fMRI During Seizures

Integrating EEG/fMRI offers a unique approach of characterizing brain activity. The combination of high temporal resolution EEG and high spatial resolution of fMRI add to enhance the localization of rapidly developing epileptic sources in the brain. It Demonstrate BOLD changes associated with epileptiform discharges and localize generators of discharges.

III METHODS AND TECHNIQUES INVOLVED

a) Cluster –Wise Basis:

The clustering algorithm was initialized with a table containing the distances between the projected BOLD time series of any two voxels. Two of these clusters includes the visual cortex and primary somato/sensory motor cortex whereas the other two includes structures such as the inferior and middle temporal gyrus or the pre cuneus and superior frontal gyrus.

b) Local Multimodal Serial Analysis:

The potential brain function is efficiently captured by fusing EEG & fMRI in the local region. The uncertainity is decreased by emphasizing both the common subspaces of the two modalities. The weak change in BOLD signals related with EEG features are detected from signal sensitivity and superiority. Epileptic discharges associated with underlying BOLD changes is revealed with the help of local multimodal serial analyser.

c) Mapping Colour Pixels:

Noise filtration is done after recording and obtaining EEG data sets are filtered by using temporal and spatial filters. It is converted to digital format and in the next stage it is identified by a grid of combination of colours to map the full images.

d) Transfer function:

Regressors are constructed by defining the different transfer functions using the spectrum of the EEG data. A feature corresponding to the “Total power” in the scalp EEG time series, heuristic,3-band Frequency Responses obtained and summing the EEG power over all frequencies is analyzed.

e) Data Analysis:

Experimental data analysis is done using SPM2 software. The low frequency noise is removed by using high pass filter with a cut off of 128 seconds SPM2 software is used for experimental data analysis. A high pass filter with a cutoff of 128 seconds was used to remove low frequency noise. EEG-fMRI is fused and the canonical hemodynamic response function was modeled by two gamma variate functions convolved with the spike time. Finally the canonical HRF was specified as the task regressor and included in the SPM design matrix.

f) Permutation Test:

In order to judge the significance of any results for each subject and analysis strategy is done for every subject. The labels related to spikes are permuted that involves generating a random of spike timings. A distribution of all cluster values from all permutation steps will be generated from input.

g) Cosine Radial Function Neural Network:

There are two primary differences between the Radial Basis Function Neural network hidden layer nodes besides the incorporation of PCA. This classifier typically consists of one hidden layer in addition to the inputs and output layers. There is very little variation in the classification accuracy (95.8-96.6%) for a wide range of spread values (0 to 90).

h) Optimal Weighting factors:

A weighting factor reflecting MR epoch similarity for template calculation. The effects of the six tested values of w on the non-task locked EEG after IAC. With decreasing w spectral peaks, reflecting the amount of residual artifacts, decreased. For large values of w, these less identical epochs have more impact on the shape of the template and hence when subtracting the template and hence when subtracting the template more residual imaging artifact remains.

i) K- means Clustering:

A vector quantization method basically and is very popular method of cluster analysis. The initialization of the K cluster centers are chosen in a random manner. The assignment of each x corresponds to nearest cluster center c by means of Euclidean Distance is followed and compared and is expressed mathematically. Each cluster center is updated at periodic intervals as the mean of the entire x that belongs to it. These gets repeated until the cluster centers become stable and after attaining stability the process can be stopped.

j) Principal Component Analysis:

A multivariate technique which is used to analyse a particular data table where observations can be explained by the inter correlated dependent variables. The main goal is to extract the most vital information from the data table and it can be easily represented as a particular set of new orthogonal variables called principal components can be used to display and analyse the patterns of similarity of observations in a particular data set and it is used widely in almost all the scientific areas.

k) Eigenvector for Frequency Estimation:

It seperates the waveform information into two subspaces a signal subspace and a noise subspace. The eigen decomposition creates orthogonal eigen values of decreasing order. The impact of noise can be effectively degraded by removing eigen vectors which are supposed to belong to noise subspace. These methods are considered frequency estimators rather than true power spectral estimations, because they do not preserve power of the signal.

l) Non parametric method:

In this method, autocorrelation is initially estimated from a time sequenced data set. In next case power spectrum estimation by applying FT to the autocorrelation sequence. A data window is applied to each segment of the time sequences to divide the time sequence into successive blocks and finally the periodograms are averaged over time to determine the power spectral density

m) Parametric method:

The spectral discharge which is the major disadvantage of non parametric method can be overcome by parametric or model based power spectrum estimation methods. Better frequency resolution can be obtained. The signal is assumed to be a stationary random process. The signal is then modeled at the output of a filter for which white noise is the input. Burgs method for normal, interictal and ictal segments.

n) Wavelet Transform:

A wavelet is a small wave of finite duration and finite energy which is correlated with the EEG signal to obtain the wavelet coefficients. First the mother wavelet is shifted continuously along the time scale to obtain a set of coefficients at all instants of time. The wavelet coefficients represent both the signals in time and frequency domains. Next the wavelet is dilated for a different width and then normalized so as to contain the same amount of energy as the mother wavelet. Then the first process of shifting this dilated wavelet along the time scale and evaluating the corresponding set of coefficients is done.

o) Non linear method of analysis:

Frequency domain methods can capture rhythmic oscillations in a signal, but are limited by the inability to detect nonlinear coupling and phase locking among harmonics in the same spectrum. Biological systems can be represented in an effective way using nonlinear techniques. This is true for EEG signal analysis too. The various useful and tried nonlinear parameters for the detection of epilepsy using EEG signals are HOS, Largest Lyapunov Exponent, correlation dimension fractal dimension, hurst exponent, entropies like approximate entrophy and sample entropy and Recurrence Quantification Analysis.

p) DCM Analysis:

DCM was developed for (and applied principally to) estimating coupling among brain regions and how that coupling is influenced by experimental changes (*e.g.*, time or context). The basic idea is to construct reasonably realistic models of interacting (cortical) regions or nodes. These models are then supplemented with a forward model of how the hidden states of each node (*e.g.*, neuronal activity) map to measured responses. This enables the best model and its parameters (*i.e.*,effective connectivity) to be identified from observed data. Bayesian model comparison is used to select the best model in terms of its evidence (inference on model-space), which can then be characterized in terms of its parameters (inference on parameter-space). This enables one to test hypotheses about how nodes communicate; *e.g.*, whether activity in a given neuronal population modulates the coupling between other populations, in a task-specific fashion.

q) GLM Analysis:

The General Linear Model (GLM) is mathematically identical to a multiple regression analysis but stresses its suitability for both multiple qualitative and multiple quantitative variables. The GLM is suited to implement any parametric statistical test with one dependent variable, including any factorial ANOVA design as well as designs with a mixture of qualitative and quantitative variables (covariance analysis, ANCOVA). Because of its flexibility to incorporate multiple quantitative and qualitative independent variables, the GLM has become the core tool for fMRI data analysis after its introduction into the neuroimaging community by Friston and colleagues (Friston et al. 1994, 1995).

r) Wavelet Packet Decompositions

A wavelet transform uses wavelets, which are scaled and translated copies of a basic wavelet shape called the ‘mother wavelet’ to transform the input signals. Mother wavelets are functions that are localized in both time and frequency and have varying amplitudes during a limited time period and very low or zero amplitude outside the time period. Wavelet transform yields wavelet coefficients that represent the signal in both the time and frequency domains.

s) Extreme Learning Machine:

Feed forward neural network for classification or regression with a single layer of hidden nodes, where the weights connecting inputs to hidden nodes are randomly assigned and never updated (i.e. they are a random projection). The weights between hidden nodes and outputs are learned in a single step, which essentially amounts to learning a linear model. All the parameters of the traditional feed forward neural networks need to be tuned commonly by the gradient based learning algorithm. However with the goal of better learning performance, the procedure of training the neural networks are repeated so many times that the learning speed is extremely slow and it is easy to fall into local optima.

t) Fuzzy Clustering:

Fuzzy clustering (also referred to as soft clustering) is a form of clustering in which each data point can belong to more than one cluster. Clustering or cluster analysis involves assigning data points to clusters such that items in the same cluster are as similar as possible, while items belonging to different clusters are as dissimilar as possible. Clusters are identified via similarity measures. These similarity measures include distance, connectivity, and intensity. Different similarity measures may be chosen based on the data or the application.

u) Support Vector Machine:

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a no probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.

v) Empirical Mode Decomposition:

A Predefined basis function is needed in case of fourier and wavelet based methods to represent a signal. No priori knowledge is required in case of EMD as it relies in a fully data driven mechanism. EMD is applicable for linear, nonlinear, stationary signals such as biomedical signals. The major idea behind EMD is the decomposition of a signal into sum of intrinsic mode functions. An IMF is defined with zero crossing envelopes with equal number of extrema with all local maxima and minima being symmetric with respect to zero.

IV DISCUSSION AND FUTURE WORK

The complex neural system is composed of billion of neurons in the human brain connected together with the axion and synapses. The simple linear superposition of the neurons is not equivalent to the function of the neural system. The brain electrical activities are very complex and dynamic. An Automated system is needed to detect the nature of the seizures at the early stage to detect and classify normal, ictal and intractical state may help improve the quality of life by preventing its occurrences. There is still a lot of unanswered questions that need to be addressed. properties.

V CONCLUSION

In Conclusion, Epilepsy is a neurological disorder that can cause serious discomfort to the patients due to its abrupt and uncertain nature of presentation. Simultaneous EEG-fMRI mapping helps us to get better understanding of brain dysfunctions and brain activity. To help researchers better analyze EEG-fMRI signals, various signal analysis techniques such as linear, frequency domain, time- frequency, non linear methods are discussed in this review. This combined modality helps us to gives better information and insights of human brain. ICA could be useful tool to better understand the spatiotemporal evolution of the generators in focal seizures with different EEG patterns, providing insights into their physiopathogenesis. These methods have significant room for the improvement as well as large variety of application.

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