Source Imaging of Simple Finger Movements Captured During Auditory Response Tasks

Estimation of Variation in Neural Information Flow under Varying Vigilance Levels

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Abstract— **Neural Information Flow during simple cognitive or motor actions is very recent research topic. One of the simple movements to be studied is a simple finger movement. In this paper, Electro-encephalograph (EEG) Source Imaging has been used to model the Neural Information flow, during performance of a simple Auditory Response Task (ART). The estimated sources are firstly divided into separate scouts according to the Destrieux Atlas. Then, relative power carried in each scout at each instant has been used to create a neural information flow map. Another key feature of this paper lies in the fact that the database corresponded of subjects performing a group of tasks repetitively until significant drop in vigilance. This provides a unique point of view, as to how drop in vigilance levels affect the Neural Information flow. The results show a correlation between trends reflected in EEG parameters and performance scores of neuropsychological tests.**

Keywords-Source Imaging; Simple Finger Movements; EEG; Auditory Response; Neural Information Flow

I. Introduction

The electrical signals generated by the brain, from the prenatal stage, through the entire life of a human being, represents not only the brain activity, but also, the status of the whole body[1]. Cortical neurons align themselves in columns orthogonal to the cortical surface[2]. When a large group of such neurons polarize or hyperpolarize in close synchrony, we obtain dipolar current sources oriented orthogonal to the cortical surface. Characterization of variation in neural activation patterns under various cognitive and motor action states is a very engaging area of research to many experts across the world.

Use of source imaging methods has been a major point of focus in recent years for neuroscience and clinical electro-encephalography research. Source imaging or source localization involves starting from some initial distributed estimate of the source and then iteratively reweights. This method is implemented, for example, in the Focal Underdetermined System Solver (FOCUSS) algorithm[3]. Another such example is the LORETA algorithm[4].

Another source localization approach incorporates a priori assumptions about the sources and their locations in the model. Electric current dipoles are usually used as sources, provided that the regions of activations are relatively focused[2]. A third approach is a spatio-temporal model based source localization approach[5]. The main assumption of the spatiotemporal model-based approach is that there are several dipoles, with fixed position and orientation but varying strength (amplitude) [5], [6].

Distributed source localization, based on algorithms such as – sLORETA, weighted Minimum Norm Estimate (wMNE)[7] etc. is a characteristic problem of distributed source models where a large number of unknown quantities have to be estimated from a much smaller number of measurements. Linearly constrained minimum variance beamforming [8], or spatial notch filter [9] based approaches consists of a blind deconvolution based solution to the Source Localization problem.

Especially of interest is the study of motor actions through Source imaging methods. Repetitive transcranial magnetic stimulation of primary motor cortex in piano players, supports evidence of major involvement of motor cortex (MI) in generation of complex finger movements[10]. Study of Bereitschaftspotential (BP) with high resolution direct current (DC) EEG, showed the primary role supplementary cingulate cortex (SCMA) plays in generation of trigger for voluntary complex movements[11][12]. BP is found to be bilaterally spread over parietal, pre-central cortex and the midline; whereas, the Motor Potential (MP), remains largely restricted in contralateral motor cortex [13]. Study of Motor area's with high density EEG and functional magnetic resonance imaging (fMRI) shows, activation of MIs [14]. Joint use of EEG-fMRI to study the blood oxygenation level dependent (BOLD) signal are found to be highly correlated with Event Related Desynchronizations (ERD) in the regions of activation [15]. In fact, though Event Related Potentials (ERP) tend to be phase locked with an external trigger event, whereas ERDs are not

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thought to be so, leading to an even more prominent involvement of MI [16]. Functional cooperativity study during simple finger movements, indicates activation of the contralateral primary motor cortex, the homologue part of the primary sensory cortex, the supplementary motor area (SMA) and the lateral premotor areas, in all volunteers [17]. Source imaging using Magnetoencephalography (MEG) of regular string instruments players shows significant difference in cortical activations for left hand control [18]. Brain surface current density (BSCD) reconstructions revealed involuntary motor activity involving the contralateral primary motor cortex (M1) [19]. Dynamic Causal Modelling (DCM) based network characterization emphasized a grip related coupling between the SMA and M1[20]. Human manual motor control involves task-specific modulation of inter-regional oscillatory coupling both within and across distinct frequency bands, as inferred in [21]. Readiness Potential (RP), a preceding potential for voluntary motor movements, can be extracted by constrained source separation [22]. Selective Modulation of SMA, affects RP generation, as evidenced by [23]. A classification problem based on single trial EEG for motor tasks has potential applications in Brain Computer Interfacing [24]. Changes in Sources during simulated driving is also measured by entropy measures [25].

Alertness in human beings may be defined as the state of paying close and continuous attention. Several approaches have been reported in literature to track the change in level of alertness of human beings using physiological signals. The major contributions of this work are as follows:

- A novel design of the Auditory Response Test (ART), an improvement over similar experiments reported in literature
- EEG Sources during participation in the ART task
- Neural Information flow computed by relative power carried at each instant by each region
- Observations in changes in the neural information flow path, from analysis of EEG sources under varying stages of vigilance.

II. Experiment Design

The experiment is designed to induce a gradual drop in alertness/vigilance levels of an individual through continuous repetition of identical cognitive tasks[26] without significant rest/pauses in between. A total of 8 subjects, including males and females in the age group 25 to 30 years were selected from graduate students and employees at Indian Institute of Technology, Kharagpur, India. Use of stimulants such as tea, coffee etc. was restricted at least four hours prior to the experiment. Subjects were adequately rested before the onset of the experiment.

The test schedule for the experiment consisted of tasks that required sustained attention for extended periods of time and assessed the changes in various cognitive faculties. The test battery comprised of:

- Stroop Task [27],
- Letter Counting Test [28]
- Psychomotor Vigilance Test (PVT) [29] comprising of an Auditory Response Test (ART) and a Visual Response Test (VRT).

A. *ART Task*

This particular design involved reaction of the subjects to a random sequence of 1 and 0, with length in between 30 to 50; with randomly chosen interval between two consecutive stimuli, in the range of 2 to 3 second. The Sequence was presented two times in each stage, in a straight and a reverse run. On presentation of the stimulus, the subjects were instructed to press 1 or 0 with index and middle finger respectively, on a keyboard present before the subject on the straight run. On reverse run, they were required to press 0, when hearing 1 and vice-versa. This essentially introduced complexity in the task. The keyboard was mechanically configured to interact with an event marker, connected with a 64 channel PSG, developed by RMS India, which ensured the reaction locations to be more or less synchronized.

III. EEG Signal Processing

A. *EEG Recording*

The present study uses the 2 minute EEG recording during ART in the straight run for the proposed analysis.

B. *EEG Preprocessing*

Raw EEG data is contaminated with artifacts, generally characterized by amplitudes in the mili-volt range (whereas the actual EEG is in microvolt range) in the frequency band of 0-16Hz [2]. The high frequency noise includes atmospheric thermal noise and power frequency noise and in-band/ low frequency noise is caused primarily by eye movements, respiration and heart beats [30]. The EEG signals were filtered using a band-pass least squares FIR filter of order 24 with cutoff frequencies of 0.4-30 Hz. DC bias removal is done to center the signal at zero. Finally, the in-band artifacts were then removed using wavelet Thresholding [31]).

C. *The EEG Source Imaging, problem definition for implementation of sLORETA*

The main tool in the adapted process was ‘‘standardized Low-resolution Brain Electromagnetic Tomography’’ (sLORETA) algorithm, proposed by[32]. This approach starts from a rectangular grid of N_v voxels covering the cortical gray matter and obtains inverse solutions confined to these voxels. The present paper uses a discretization level of $N_v = 1485$. At each voxel, a local three-dimensional current vector is assumed as

$$j(v,t) = \left(j_x(v,t), j_y(v,t), j_z(v,t)\right) \quad (1)$$

where v is a voxel label, t denotes time.

The column vector of all current vectors (i.e., for all gray-matter voxels) can be denoted by

$$\boldsymbol{J}(t) = \left(j(1,t), j(2,t), \ldots, j(N_v,t)\right) \quad (2)$$

The EEG at each electrode may be denoted by $y(i,t)$, where i is an electrode label and t denotes the time; the n_c dimensional column vector composed of all the electric potentials at all available electrodes shall be denoted by

$$\boldsymbol{Y}(t) = \left(y(1,t), y(2,t), \ldots, y(n_c,t)\right) \quad (3)$$

For distributed source models, it is possible to approximate the mapping from $\boldsymbol{J}$ to $\boldsymbol{Y}$ by a linear function[33], whence it can be expressed as

$$\boldsymbol{Y}(t) = \boldsymbol{KJ}(t) + \epsilon(t) \quad (4)$$

Here $\boldsymbol{K}$ denotes a $n_c \times 3N_v$ transfer matrix, commonly called ''lead-field matrix''. This matrix describes properties of the head model, which is constructed by 3 sphere fitting method, based on Boundary Element Method(BEM)[34], using the brainstorm software [35], available at [36].

$\epsilon(t)$is a vector of observational noise assumed to be white and Gaussian with zero mean and covariance matrix $C_\epsilon = E(\epsilon\epsilon^T)$ such that C_ϵ has the simplest possible structure, namely

$$C_\epsilon = \sigma_\epsilon I_{n_c} \quad (5)$$

Where I_{n_c} denotes the $n_c \times n_c$ identity matrix; that is, it is assumed that the observation noise is uncorrelated between all pairs of electrodes and is of equal variance. The sLORETA problem can be solved by performing a convex optimization of functional $\mathscr{T}$based on a regularization parameter α, with this simple step, as discussed by [37].

$$\mathscr{T} = \sum\left(\frac{diag(A \times A^T)}{trace\left(\left(I_{N_c} - K \times T\right)^2\right)}\right);\ \text{where } \mathbf{A} = \|\boldsymbol{KJ} - \boldsymbol{Y}\|^2; \quad (5)$$

Explicit solution yields the inverse operator, *T*.

$$\boldsymbol{T} = \boldsymbol{S_{\hat{J}}} \times \boldsymbol{K^T} + \boldsymbol{\alpha H};\ such\ that\ , \boldsymbol{\hat{J}} = \boldsymbol{TY} \quad (6)$$

Here, $\boldsymbol{S_{\hat{J}}}$ denotes the autocovariance of Estimated Source Current Density, assumed to be identity during optimization. A proper α is chosen by convex optimization, based on which the inverse operator is computed.

D. Construction of Scouts

Scouts have been constructed on a total of 147 areas, based on the Destrieux Atlas [38][39]. The full description of said atlas is freely available under the GNU public license, and as the part of the software Freesurfer, available at [40]. Below, a figure with only a few certain Destrieux area's is given in Figure 1.

Here "G and S occipital inf L" corresponds to the left hemisphere inferior occipital gyrus, "G and S cingul Ant" refers to the ACC in right, left and middle, and midline posterior respectively. "G and S fronto-margin R/L" refers to the fronto marginal gyrus of Werniks and sulcus.

E. Relative Power Computation and Path Costruction

At each instant the relative power carried by scout *k*, is computed as follows –

$$Rel\_J_k = \frac{\sum_{v \in k} \widehat{J_v}^2}{\sum \hat{J}^2}; where\ v = voxels\ in\ simulated\ space.$$

At each instant this Relative power by each scout is stored. Then Maximum Relative powered regions are connected to create the paths.

IV. Results and Discussion

The results for the variation of neurophysiological and neuropsychological parameters with varying alertness levels have been presented in this section. For the ease of description the results has been divided into Non-EEG Parameters and EEG parameters.

A. Non-EEG Parameters

Figure 2 shows the variation of average time (in seconds) required to complete the LC task. The time required has an indeterminable trend, showing both increase and decrease; which is mainly due to intra-subject variation.

Variation of subjective alertness scores (average across subjects) is shown in Figure 3. An interesting observation is that the scores show an initial increase, followed by some saturation in the middle stages, before a drop due to cognitive fatigue. An increase in the final stages can be explained by an attempt on the part of the subjects to force their attention due to psychological feedback and hence have reported a higher alertness on a scale of 1 to 10.

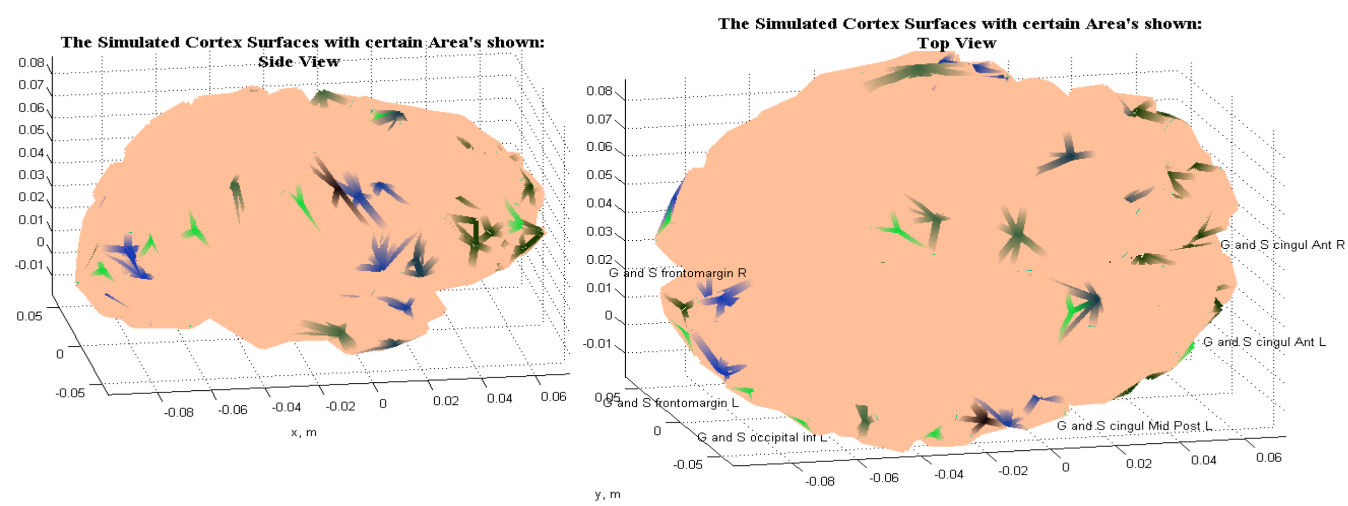

Figure 1: Simulated Cortex area with certain Destrieux Area's marked.

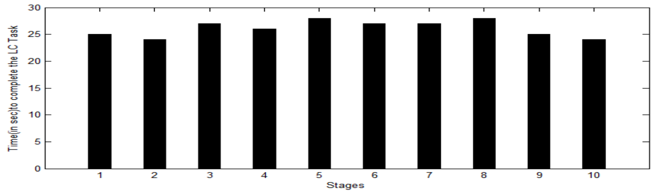

Figure 2: Variation of average time required to complete the LC Task (in seconds)

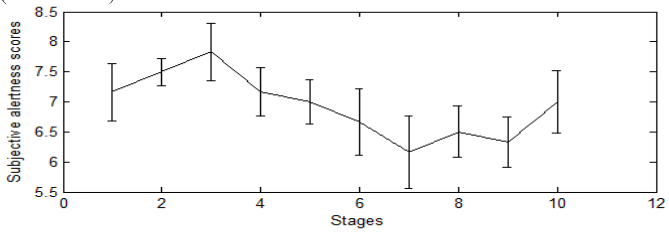

Figure 3: Variation of subjective alertness scores for subjects

B. EEG energy and entropy Parameters

The mean energy for subjects in the theta and alpha bands show a gradually increasing trend with increased cognitive loading shown in Figure 4.

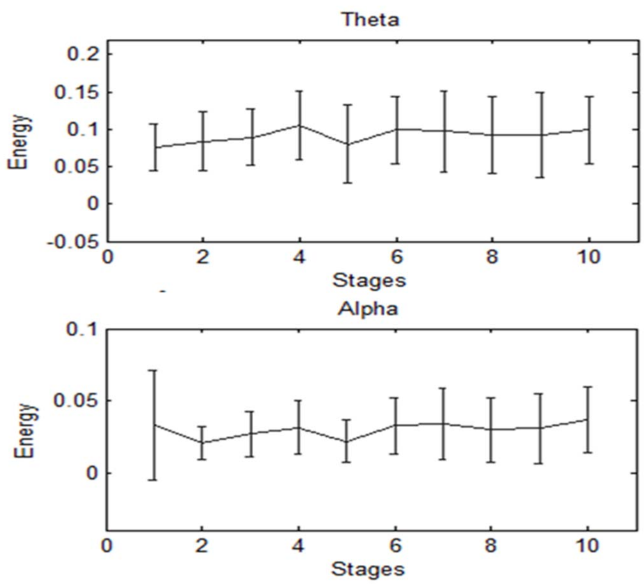

Figure 4: Error bar plot of Variation of Theta and Alpha Band Energy

C. Neural Information Flow paths

The most common path in the first few stages are found to be starting from Occipital poles; or rather the most active scouts at first were shown to be near occipital lobes. This might be due to active visual field of the subjects. It might be due to the self-awareness of the subjects and due to relative unfamiliarity with the experimental space and structure. The next activated region in most cases was orbitofrontal cortex (OFC), very close to the orbital gyri's. OFC is thought to be associated with decision making; indicative of the decision making required by the subject during the performance. The Next activated region was Superior frontal gyrus, indicative of working memory functioning [41]. The path ends at insular gyrus, as shown in Figure 5.

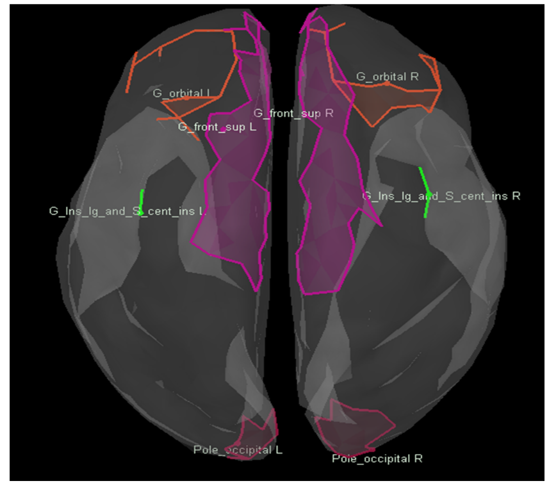

Figure 5: Common Path for 1st stage

During the 5th stage, however, there was increased power in Superior frontal Gyrus. Closely following was the middle frontal gyrus, indicative of loading for "yes/no" decision making [42]. Finally activation was in superior temporal sulcus [43].

Markedly different was the involvement of Superior Parietal Lobule[44], and the central sulcus; indicative of extra effort in visual attention.

V. CONCLUSION

The present work shows an novel investigation of EEG synchronization of brain regions in conjunction with several psychological measures of alertness. The uniqueness in this experiment lies in the use of stimuli as both task and tool on the cognitive test. EEG measurement associated with the experiment is of varied nature. Simple energy and entropy measures computed from EEG shows very similar trend to the trends observed by psychological tests as well as with the self-evaluation of the subjects.

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