

Group-Based EEG Source Mapping of the Visual Cortex Using Adaptive MSP Localization

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ABSTRACT

Approximately 10–20% of the global population (~8.2 billion in 2025) is affected by neurological disorders, including migraine (~12%), Alzheimer’s/dementia (~0.7%), epilepsy (~0.6%), and Parkinson’s disease (~0.1%). Electroencephalography (EEG) serves as a critical modality for capturing electrophysiological brain dynamics in such conditions. Advanced engineering techniques—including inverse problem regularization, spatial filtering, source reconstruction algorithms, and computational modeling—enhance the accuracy, spatial resolution, and clinical applicability of EEG systems. EEG source localization, supported by biomedical signal processing pipelines, plays a key role in diagnosing and treating 10–15% of brain disorders involving abnormal cortical excitability.

This research proposes a novel computational approach to EEG source localization that emphasizes engineering innovation in biomedical signal processing and system optimization. Specifically, it targets neural activity within the visual cortex, applying a Bayesian framework with Multiple Sparse Priors inversion. The proposed algorithm employs adaptive patch variation to optimize Free Energy and reduce localization errors across subject groups in response to facial stimuli, including familiar, unfamiliar, and scrambled faces. By addressing the ill-posed nature of the EEG source localization problem, this approach mitigates uncertainties caused by factors such as noise, neural overlaps, and structural defects. The results are validated using a synthetic EEG dataset. MATLAB-based SPM12 toolbox is used for pre-processing and statistical analysis. In this study, EEG source localization was performed on six subjects (three males, three females, aged 23–31) using a proposed MSP inversion algorithm across cortical patch ranges (350–3500, step 150). The adaptive patching strategy differs from prior MSP work by dynamically adjusting patch sizes to optimize Free Energy, thereby reducing localization errors more effectively across subject groups.

The proposed MSP inversion achieved reliable EEG source localization, with mean errors ranging from 1.2 to 7.7 mm and a group mean of 4.0 mm, consistently identifying occipitotemporal regions (BA 18, 19, 20, 37). The demonstrated results confirm the accurate localization of visually evoked sources, supporting its potential for diagnostic and computational applications in biomedical engineering and neuroscience.

1. Introduction

The human brain, a highly intricate bio-computational system, controls the essential functions including perception, memory, language, emotion, and motor control. It comprises approximately 86 billion neurons that communicate through electrochemical signalling, producing electrical activity measurable via scalp-mounted electrodes[1]. This electrical activity is assessed by various neuro electro-imaging techniques including Electroencephalography (EEG), Magnetencephalography MEG, Positron Emission Tomography (PET) and Magnetic resonance imaging (MRI) [2]. However, accurate and reliable brain source localization remains a challenge due to the inherently ill-posed nature of the inverse problem, limited spatial resolution, signal noise, and inter-individual anatomical variability [3,4]. Although multimodal neuroimaging and high-density electrode arrays improve brain source localization accuracy, EEG provides millisecond temporal resolution for real-time brain activity analysis [5]. The portability and wearability of EEG make it well-suited for biomedical research and diverse applications such as brain-computer interfaces (BCI), neuromarketing, and neuro-ergonomics [6]. EEG is widely used for diagnosing brain disorders such as epilepsy, Alzheimer's, and Parkinson's. It is cost-effective, portable, and non-invasive, although it can be sensitive to noise, artefacts, and variations in scalp properties. It identifies brain activity sources using forward and inverse modeling techniques to calculate scalp potentials and localize neural generators [7]. EEG source localization employs head models that represent the brain, skull, and scalp as concentric layers with anisotropic conductivity. This Berg approximation is commonly used in three- and four-layer models as shown in Fig.1. Since each subject's head has unique anatomical and conductive properties, subject-specific head models are necessary for accurate source localization.

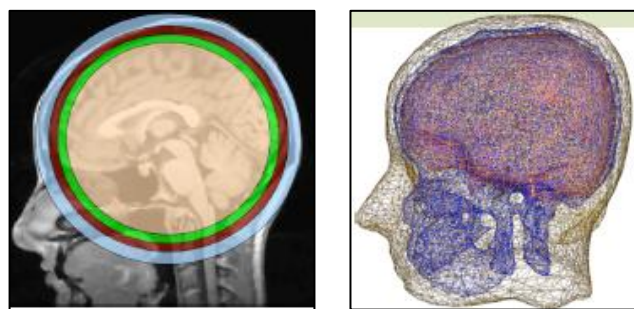


Fig. 1. Head Modeling Approaches used in EEG source Analysis

Approaches such as Boundary Element Method (BEM) and Finite Element Method (FEM) offer improve the accuracy but require higher

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computational loads, as shown in Fig.2. Sensor-fitted sphere models provide a balance between anatomical accuracy and computational efficiency. BEM models the head as a three-layer conductor and uses simplified conductivity in integral methods to improve efficiency [8,9].

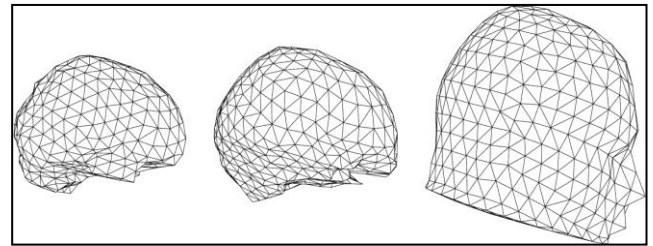


Fig. 2. Head Model meshes for EEG forward computation – BEM using closed triangular surface meshes for scalp, skull and brain

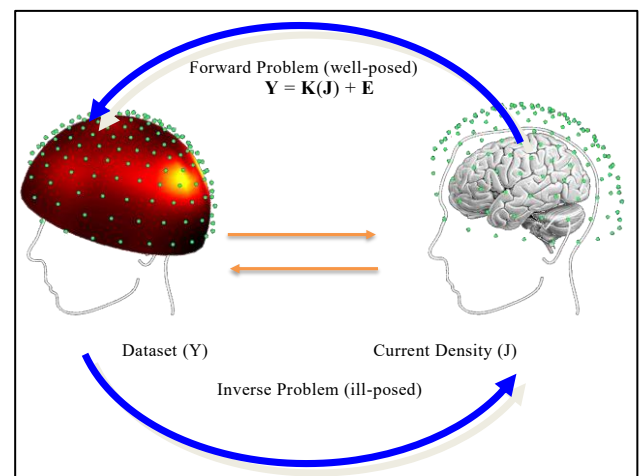


Fig. 3. Forward and Inverse Models

The forward model uses BEM to measure potentials generated at the scalp, whereas the inverse model estimates neural sources within the brain[10, 11] as illustrated in Fig.3. However, since it is an ill-posed problem, obtaining a unique solution is challenging, as different source configurations can produce identical scalp measurements [12].

To address these challenges in EEG source localization, various advanced algorithms have been developed by neuroscientists and engineers[13, 14]. For example, Minimum Norm (MN) estimates neural sources by minimizing the overall power of the source distribution. The Low-Resolution Electromagnetic Tomography (LORETA) family provides smooth and low-resolution estimates of brain activity. Focal Underdetermined System Solver (FOCUSS) is designed for underdetermined systems used for sparse source localization. Recursive Multiple Signal Classification (MUSIC) identifies multiple signal sources iteratively, enhancing localization accuracy. Hybrid approaches, such as Hybrid Weighted Minimum Norm, Recursive sLORETA-FOCUSS, Weighted Minimum Norm LORETA, and Shrinking LORETA-FOCUSS, combine features from multiple algorithms to improve performance [12, 15].

The Convexity - Champagne , FLEX-Anatomical patching (AP) and Patch-AP are worked upon to improve accuracy, with studies reporting lower localization errors and better alignment with true source distributions in both simulations and real EEG / MEG data[16].

Bayesian methods such as MN, Beamformer (BF), and LORETA-like approaches enhance source estimation by incorporating prior knowledge, while Multiple Sparse Priors (MSP) inversions further constrain and regularize the solution [17, 18]. These techniques are widely applied in clinical diagnostics and neuroscience to analyse dynamic brain activity. MSP also reduces the noise and improves the localization accuracy by adjusting to individual anatomical variation[19, 20].

This paper, specifically targets the visual cortex-particularly the occipital lobe, responsible for visuo-spatial coordination and the processing of visual input such as shape, motion, and contrast. Visual stimuli evoke synchronized neuronal responses in this region, producing dipolar currents, measurable at the scalp[21, 22]. This study investigates optimal source estimations in the visual cortex using patch-based MSP inversion, where the model adjusts free energy for different patch sets to achieve accurate localization while maintaining computational efficiency. Cortical patches ranging from 250 to 3500, in increasing steps of 150, were evaluated. Source estimations were derived from EEG datasets (N170 ERP) involving facial stimuli. Localization accuracy was validated using synthetic EEG generation models. The results were quantified to assess the effect of varying patch distributions on the quality of source reconstructions [23]. The study focuses on the N170 ERP component associated with facial processing. The validation is carried out through simulations using MATLAB's SPM12 toolbox. The research is also focused on calculating localization errors[24]. To calculate localization errors, MNI coordinates, computed from proposed MSP algorithm, are subtracted from true MNI coordinates computed, either from standard MSP inversion approach or fMRI by using the Euclidean distance formula for two points $P_{true} = (x_t, y_t, z_t)$ and $P_{est} = (x_e, y_e, z_e)$ in MNI space (mm):

$$Localization\ error = \sqrt{(x_e - x_t)^2 + (y_e - y_t)^2 + (z_e - z_t)^2}$$

where P_{est} represents the MNI coordinates obtained from MSP inversion by varying the patches, while P_{true} is considered the true MNI spaces.

This research paper is comprised of seven sections: Section 1 introduces the background of EEG source localization. Section 2 is about mathematical

equations used in EEG source localization. Section 3 focuses on the novelty of the proposed algorithm of adaptive patch variation approach blended with synthetic EEG dataset generation scheme for its validation and methodology adopted. Section 4 is about the outcome of results and discussion. Section 5 gives the conclusion about the research carried out in the paper. Section 6 provides future work to be carried out based on the novelty of this algorithm. Section 7 is on the acknowledgement and to say thanks for the datasets provided and section 8 is about the references

2. EEG Brain Sources: Mathematical Framework

EEG uses Maxwell's and Poisson's equations to model brain activity[13]. It solves an inverse problem to estimate active brain sources, using high-density EEG systems and advanced source modeling. This process utilizes an evaluation framework with realistic head models, real and simulated EEG data, noise models and statistical accuracy[25, 26].

The use of covariance and the Bayesian Framework makes it particularly well-suited to addressing ill- posed inverse problem [21, 27].

$$Y = LJ + \varepsilon \quad 1$$

where $Y \in \mathbb{R}^{N_c N_n}$ represents measured EEG dataset of N_c sensors and N_n time samples. L is leadfield matrix. $J \in \mathbb{R}^{N_d N_n}$ represents dipoles current density or estimate brain sources. ε Indicates random noise and uncertainty.

By applying Bayes' theorem [28]:

$$P(J/Y) = \frac{P(Y/J)P(J)}{P(Y)} \quad 2$$

where $P(J/Y)$ is the posterior probability of source estimation. $P(Y/J)$ is the likelihood probability of a given source activity. $P(J)$ is prior probability of source activity. $P(Y)$ is constant probability. The maximum posterior estimate of current dipoles is recovered by applying the operator on J to get the estimated current density:

$$\hat{J} = E[P(J/Y)] \quad 3$$

where $\hat{J}$: estimated current density (brain source activity in EEG source localization)

$E[\cdot]$: Expectation Operator (average value)

$P(J/Y)$: Posterior probability distribution of (true) current density J given the measured EEG data Y (observed EEG data at the scalp sensors). The above

equation states that the estimated current density is the expected value of the posterior distribution.

The estimated current density $\hat{J}$ can be represented as:

$$\hat{J} = QL^T (\Sigma_\epsilon + LQL^T)^{-1} Y \quad 4$$

where Q : Source covariance matrix (prior covariance of brain sources), L : Lead-field matrix (forward model mapping brain sources to scalp EEG sensors). L^T : Transpose of lead - field matrix, Σ_ϵ : Noise covariance matrix (sensor noise covariance). Y : Measured EEG data vector. This is liner Bayesian Minimum – norm estimate of the source current density. In Free energy[29, 30],

$$F = \log p(Y) \quad 5$$

where, F :Free energy (a variational bound on model evidence), $p(Y)$: Marginal likelihood (probability of observing EEG data under the model). The optimization of MSP based Bayesian framework depends upon free energy equation[31, 32] as follows:

$$F = -\frac{N_y}{2} \text{tr}(C_y \Sigma_y^{-1}) - \frac{N_y}{2} \log |\Sigma_y| - \frac{N_y N_a}{2} \log(2\pi) - \frac{1}{2} \left(\text{tr}(\hat{h} - \nu)^T \Pi (\hat{h} - \nu) \right) + \frac{1}{2} \log |\Sigma_h| \Pi$$

where F : Variational free energy, N_y : Number of samples based upon time points or trials, N : Number of EEG channels (sensors), C_y : Empirical data covariance matrix, Σ_y or $(LQL^T + \Sigma_\epsilon)$: Model covariance matrix, $\text{tr}(\cdot)$: Trace of a matrix (sum of diagonal elements), $|\Sigma_y|$: Determinant of Σ_y , $\hat{h}$: Estimated hyperparameters, ν : prior mean of hyperparameters, Π : prior precision matrix (inverse covariance of hyperparameters), $(\hat{h} - \nu)^T \Pi (\hat{h} - \nu)$: Distance of hyperparameters from the prior mean), Σ_h : Posterior covariance of hyperparameters, $|\Sigma_h \Pi|$: Determinant of the product of posterior covariance and prior precision. Free energy is not a physical energy but a log-evidence bound. Since log-likelihood can be small subtracting complexity often makes Free energy negative[33]. Free energy has no units; however, it is expressed with a negative sign[34]. Therefore, it is referred to as negative Free energy[31]. Free Energy in MSP-based EEG source localization is statistical score that balances data fit and model simplicity. Even if, negative, model with highest free energy is considered the most reliable explanation of EEG data[35].[36].

3. EEG Datasets and Methodology

3.1 Proposed Algorithm

In this research, a comprehensive MSP-based framework is proposed as illustrated in Fig 4. Visual-stimulated EEG datasets have been processed using SPM software to acquire optimized EEG brain source localizations by optimizing free energy and minimizing Localization errors[37]. The proposed framework is integrated with synthetic EEG dataset generation scheme to evaluate and validate the brain sources and their localization. Fig 4 presents a dual-pipeline flowchart comparing EEG source localization using real (left) and synthetic (right) EEG datasets. Both workflows follow parallel steps: inverse modeling, imaging methods, facial stimuli application. EEG source localization algorithms (Beamformer, MNE, LORETA-like, GS, and MSP patch variations) are applied. The synthetic pipeline includes source selection, noise addition, and D-object updating. Both branches compute Free energy and MNI coordinates, leading to a final statistical analysis of localization error sources accuracy.

3.2 Data Availability

In this research, multimodal EEG datasets were acquired upon request via email along with NOC from Prof. Dr. Richard Henson, Director of Medical Research Council (MRC) at University of Cambridge, UK. These datasets were voluntarily provided by healthy employees of MRC. The datasets include fMRI and MRI images with 1x1x1 mm³ resolution, as well as EEG dataset recorded at 1100 Hz, collected using a Elekta Neuromag Vectorview MEG system with 102 magnetometers, 204 gradiometers, and 70 EEG electrodes [38], as shown in Fig 5.

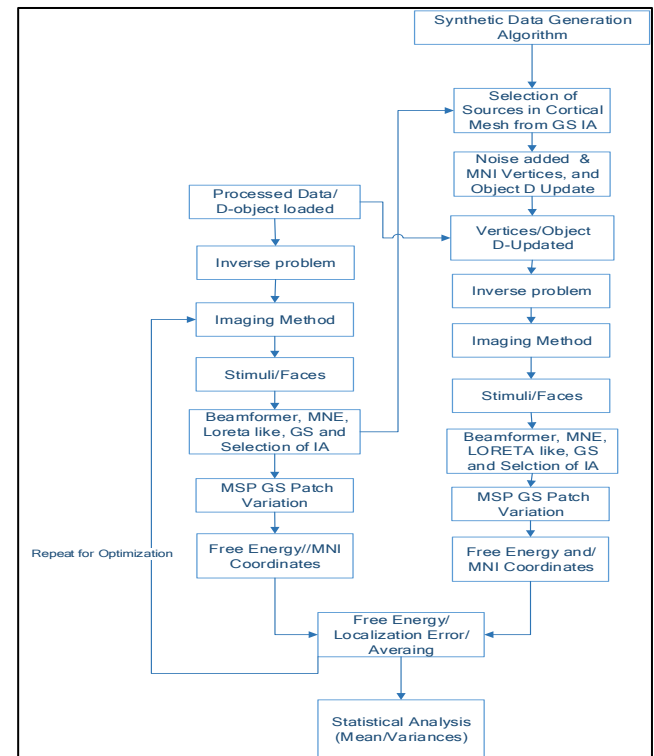


Fig. 4. Proposed Algorithm Integrated with Synthetic Data Generation Scheme

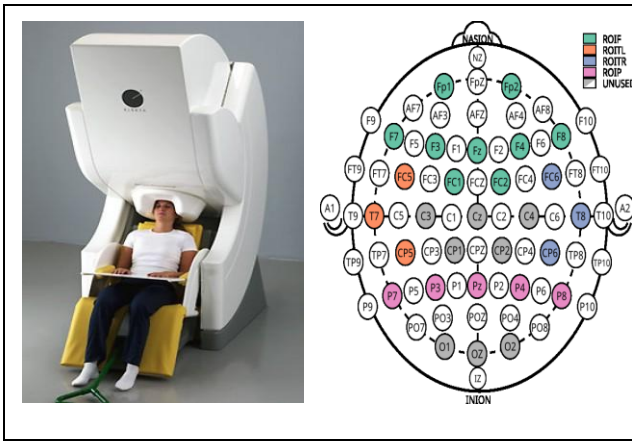


Fig. 5. Elekta Neuromag Vectorview MEG and 70 Electrodes systems [30]

3.3 Subjects / Participants

In this research, six (06) subjects - including three (03) females and three (03) males aged between 23-and 31 years, were selected to investigate optimized EEG source localization in brain visual cortex, as shown in Table 1. All participants were of Caucasian origin.

Table 1

Subjects selected

Subjects	1	2	3	4	5	6
Gender	M	F	F	M	F	M
Age	31	26	23	23	24	30

3.4 Experimental Datasets

Multimodal datasets were recorded after participants viewed familiar, unfamiliar, and scrambled faces with varied attributes, shown individually on a screen 1.3 meters away. Stimuli were presented sequentially with crosshair (+) and circle (O) signs, as outlined in Fig.6.

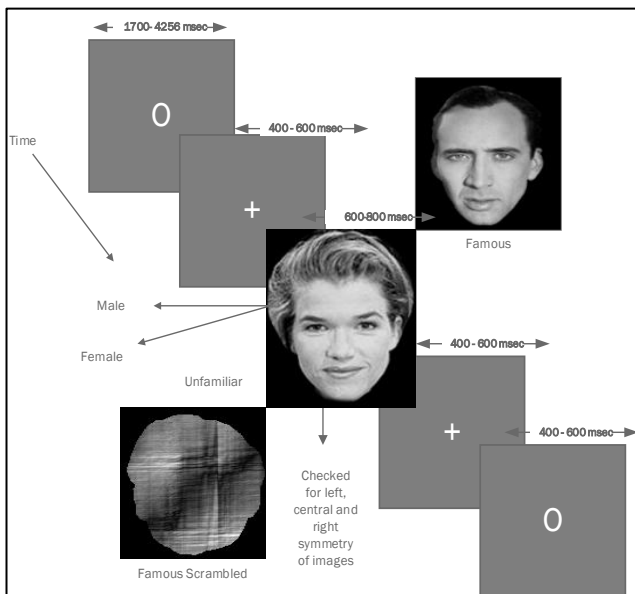


Fig. 6. Experimentation Setup for recording data

3.5 Brain Software / toolbox used

In this research, MATLAB-based SPM12 toolbox was utilized for its advanced capabilities in pre-processing, analyzing, and interpreting multimodal datasets. These included integration of fMRI, MRI and EEG for brain activity reconstruction.

3.6 Pre-processing EEG datasets

Famous Faces, Unfamiliar Faces, and Scrambled Faces, the three (03) visual stimulation conditions used, were exposed in front of the subjects to record multimodal datasets including EEG datasets. Each trial was linked to particular time intervals and conditions. To investigate brain sources localization, multiple channels with electrodes were used to measure scalp activity, which was later reconstructed into source space within the posterior occipital lobe of the brain. First, the raw EEG recordings were imported into MATLAB and converted to SPM format. The raw data was cleaned up and prepared during pre-processing. To promise accurate analysis, a thorough pre-processing pipeline of sixteen (16) steps was implemented, ranging from conversion to SPM to specifying contrasts in order to acquire cleaned EEG datasets [39, 40]. EEG datasets recorded were in the form of scalp topographies or time-varying waveforms.

The preprocessing of EEG data was carried out in SPM12 using a structured pipeline. Initially, raw M/EEG data files in native machine format (e.g., .fif) were converted into MATLAB-compatible format (.mat) for subsequent analysis. To minimize computational complexity and disk usage, the data were resampled from 1100 Hz to 200 Hz. A montaging step was then applied to remove contributions from non-cortical channels, specifically electrooculography (EOG) and electrocardiography (ECG) artifacts, ensuring improved signal fidelity [41]. Temporal filtering was performed using a high-pass filter to eliminate low-frequency drifts, followed by a low-pass filter to attenuate high-frequency noise. Event-related triggers were extracted from the STI101 channel, and stimulus-locked epochs were generated within a defined window (-100 ms to +500 ms) relative to event onset. Finally, multiple runs were merged and concatenated to produce a unified dataset, thereby preparing the pre-processed EEG signals for subsequent forward modeling, inverse source reconstruction, and statistical analysis.

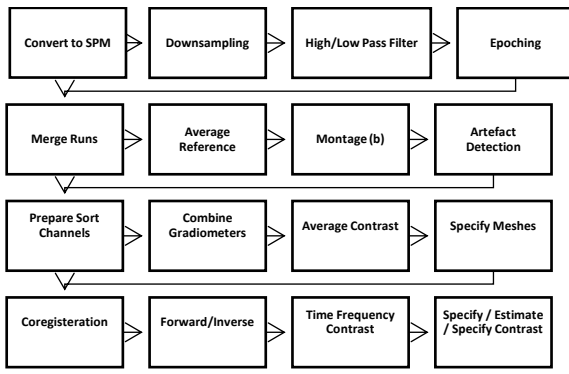


Fig. 7. EEG Pre-processing pipeline

Thus, processed EEG dataset was made available for use in forward and inverse methods for measuring scalp surface potentials, as well as brain source reconstruction and localization [Fig 8 to Fig 10].

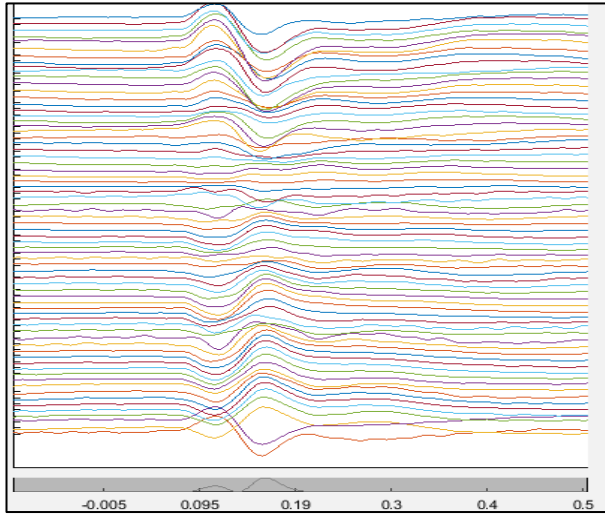


Fig. 8. Pre-processed EEG signals

Fig 8 shows the pre-processed EEG signals across multiple channels, illustrating temporal variations in brain activity. Fig 9 presents the scalp map with EEG channel placements, visually mapping electrode positions for spatial reference. Fig 10 displays the full-scale EEG response for channel EEG074, highlighting stimulus-locked brain responses over time. Together, these figures validate the quality of EEG data and its suitability for source localization analysis.

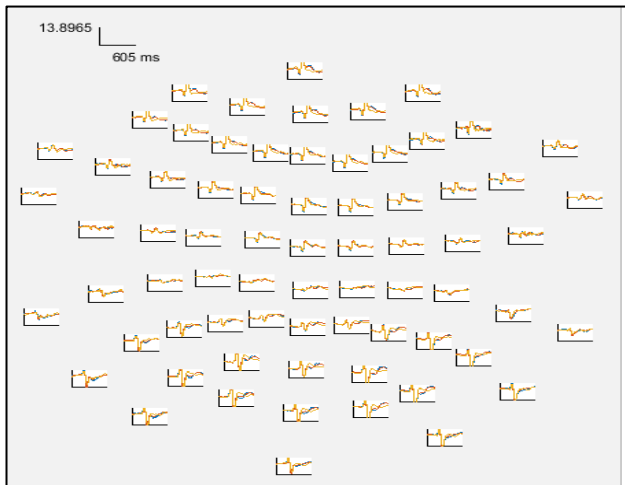


Fig. 9. Scalp map EEG signals with channels

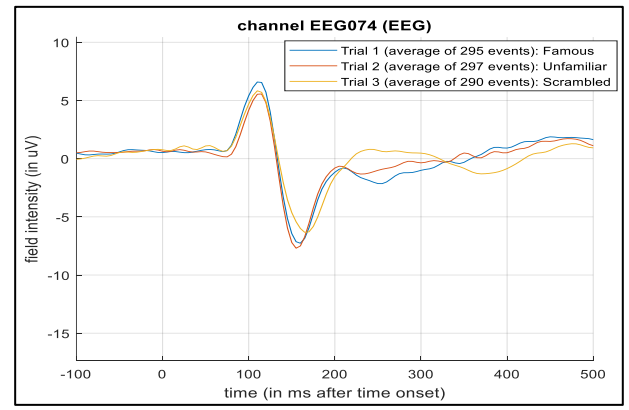


Fig. 10. Scalp map EEG 074 Channel [Full Scale View]

3.7 Forward Model

Forward model uses numerical head structures, MRI images, and a Boundary Element Method (BEM) head model, which includes co-registration of fiducial points. The lead field matrix (L) stores sensor (N) and mesh vertex (M) data in the gain matrix (K)[7, 9]. Fig. 11 illustrates the forward mechanism and output used in EEG source localizations. The flowchart begins from head volume, which includes anatomical information about the subject's brain. BEM as a numerical method is then applied to simulate electrical conductance across different tissues. The BEM model incorporates tissue conductivity and the radius of various head layers such as brain, cerebrospinal fluid (CSF), skull, and scalp. Based on this model, meshes are generated to represent the geometry of the head, using individual subject MRI data to ensure accuracy. The next step involves the computation of the lead field matrix, which maps the brain's electrical sources (dipoles) to the EEG sensor locations. Finally, neural activity voltages evoked by specific stimuli (e.g., visual stimuli) are generated to complete the forward modeling process [23].

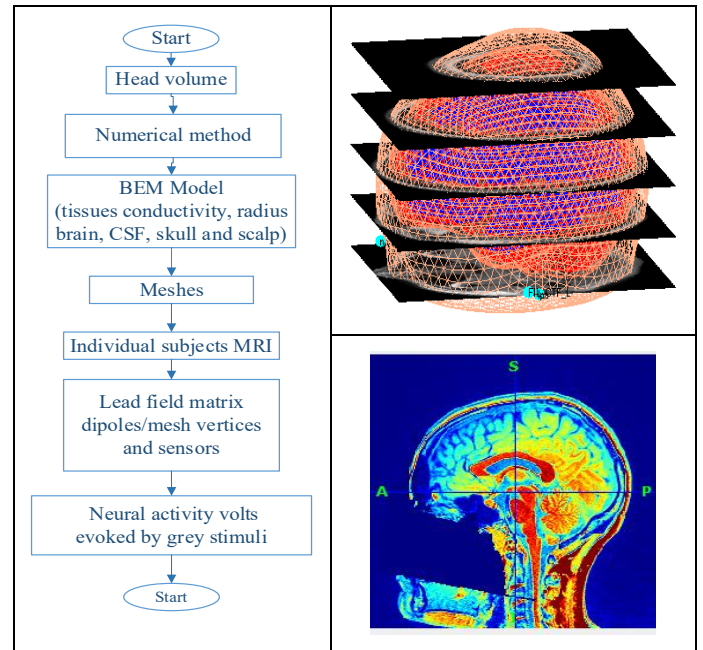


Fig. 11. Forward Mechanism and Output

Further, on the right side of Fig 11, 3D layered head, sliced horizontally, demonstrating how the different tissue layers are segmented and modeled for computational analysis, is shown. This visualization explains the spatial arrangement of tissues used in mesh generation. The bottom image is a sagittal view of the brain from MRI data, color-coded to indicate varying levels of neural activity or conductivity.

3.8 Inverse Model

The inversion modeling (Fig 2 and Fig 12) is implemented for brain source localization. It begins with loading the pre-processed data, stored in D-object containing multi-channels, trials, sampling frequency, and samples per trial [42]. The inverse problem estimates the location of brain activity based on scalp-recorded signals. Inversion techniques like Beamformer, MNE, and LORETA-like are applied, along with Greedy Search (GS) for selecting the best imaging algorithm and analysis, aligned with specific stimuli, such as facial images[43], MSP method is used with patch variation to refine source estimation. The results are evaluated using free energy and mapped to MNI coordinates. Initially best inversion approach and stimuli conditions are applied by using the assumed true default patches (250) and visual stimuli images of famous, unfamiliar and scrambled faces. This process is repeated to achieve better localization accuracy and optimized free energy [35].

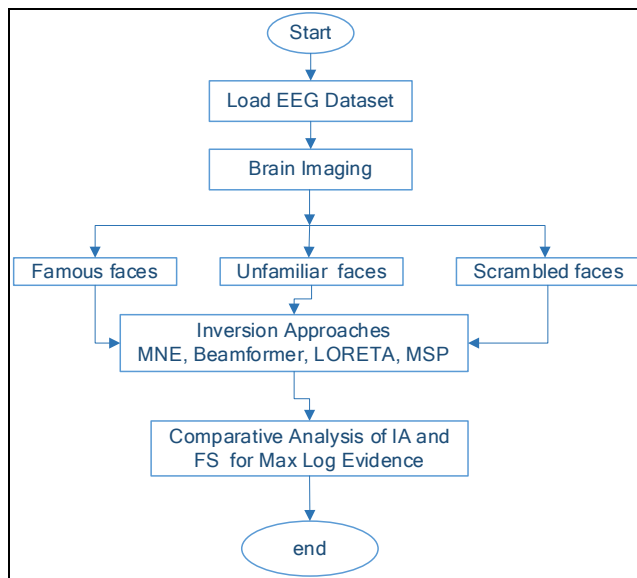


Fig. 12. Inversions

Table 2

Inversions/FE

Inversions	Free Energy
BF	-823.6
MNE	-846.3
LORETA	-841.4
MSP	-730.2

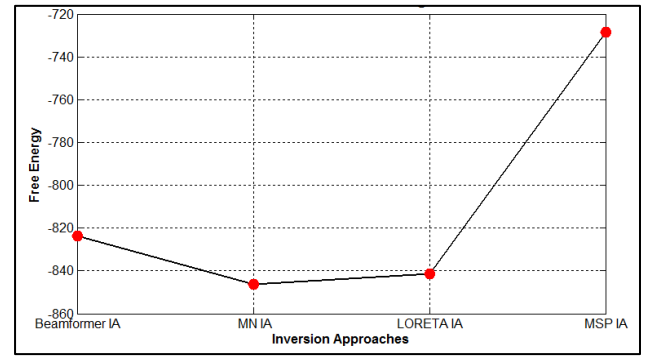


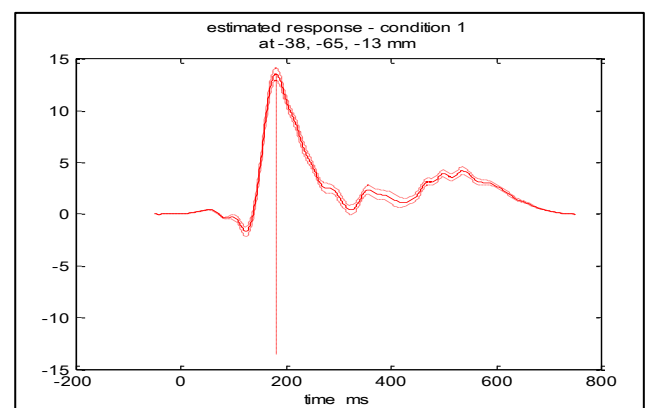
Fig 13. Free Energy and Inversion Approaches

Table 2 presents a comparative analysis of Free energy values across different inversion methods. Inversion yields the highest Free energy (-730.2) for Famous faces, indicating the best model evidence and superior fit to the data. In contrast, Beamformer, Minimum Norm Estimate, and LORETA exhibit lower Free energy (-823.6 , -846.3 , and -841.4 , respectively), reflecting less optimal solutions. This demonstrates that MSP inversion achieves more efficient and accurate source reconstruction with famous faces stimuli compared to other inversion techniques and stimuli conditions [44].

3.9 Synthetic EEG dataset Generation Scheme

A synthetic EEG dataset generation scheme is an integral part of the proposed algorithm and is employed to validate the accuracy and reliability of the source reconstruction method [10]. A forward model was used to create synthetic data by simulating scalp EEG signals using a cortical mesh, MRI template, co-registration, and lead field matrix of each individual subject. In the D-object, the synthetic data takes the place of the actual EEG while maintaining other parameters. In order to ensure that the synthetic data accurately reflects real conditions for reliable algorithm testing, MSP inversion with synthetic data is used to validate real EEG source localization accuracy [9, 35].

In Fig.14 and Fig 15 below, brain source localizations with real data and synthetic EEG data was acquired at same MNI coordinates $[-38, -65, -13]$.



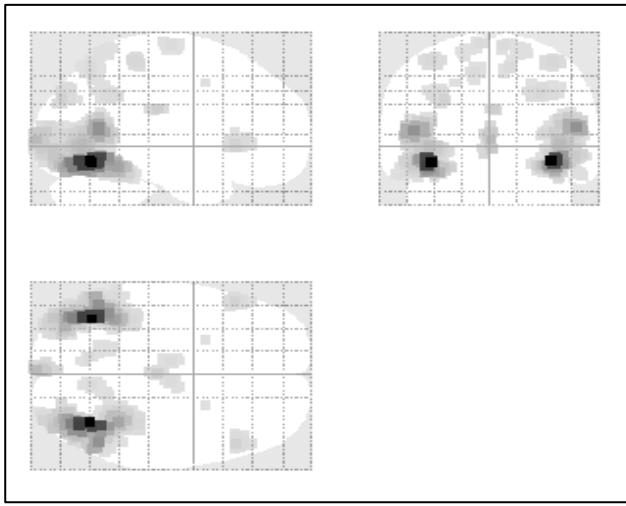


Fig. 14. Real Brain Activity at [-38,-65,-13]

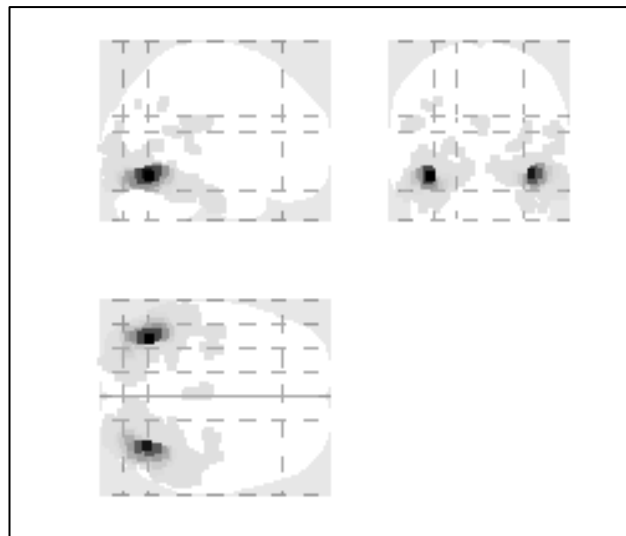
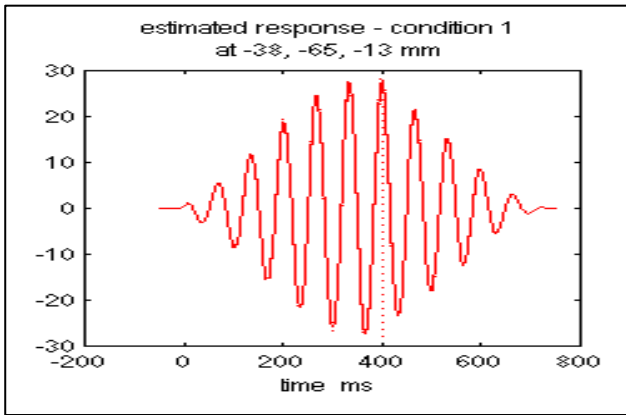


Fig. 15. Synthetic EEG activity at [-38, -65, -13]

4. Results and Discussion

In this paper, the comparative analysis of Free energy and localization errors has been performed across six (06) subjects, comprising three males (Subj #1, Subj #4, and Subj #6) and three females (Subj #2, Subj #3, and Subj #5), aged 23 to 31 years. Patches, representing regions of the visual cortex where neural sources are activated, were examined to identify optimal free energy and low localization errors. The results revealed an inversely relationship between free energy and localization errors: higher FE correlated

with lower Localization errors, and vice versa, particularly in response to familiar stimulus conditions. Furthermore, factors such as precise projections, narrow variance envelopes, and high potentials at active brain sources have been identified as contributors to optimized FE and minimized localization errors in the visual cortex.

4.1 Active Brain Sources

This section highlights active brain sources with optimized free energy and low localization errors, mainly in visual areas like the Fusiform, Visual Association, and Secondary Visual regions, while excluding irrelevant non-visual sources. In Fig.16 a pie chart representing visual stimulation illustrates the percentage distribution of EEG-evoked brain activity across various brain regions. The Right Fusiform area dominates with 50%, indicating its major involvement in the observed neural responses. Other notable areas include the Left Visual Association (25%), Left Fusiform (7%), Left-Secondary Visual (8%), Right-Secondary Visual (4%), and Right Inferior Temporal Gyrus (4%). This suggests strong activation in visual and fusiform area

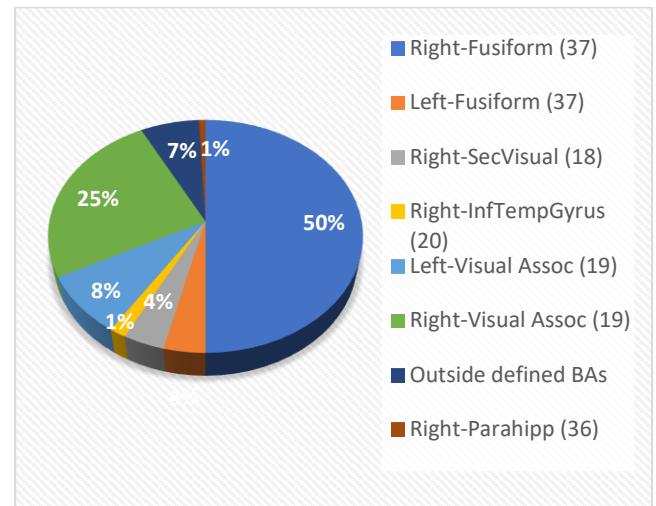


Fig. 16. Percentage of EEG Evoked Brain Areas

4.2. Free Energy at Active Brain Sources

Free energy computed from six (06) subjects from patches from 250 to 3500 is shown in Table 3 where for each subject, free energy is demonstrated against specific patches. This is done in order to show the overall tendency of generated free energy in an occipital lobe source. In MSP source localization, increasing the number of patches, can raise free energy by improving model flexibility but beyond an optimal point, additional patches are pruned and do not contribute further. Hence, only optimal subset contributes meaningfully to source estimates.

In Fig 17, six (6) lines have been plotted. In addition, red line represents an average FE against patches.

Table. 3.

Group Free Energy and Patches

Patches	Subj1 M 31	Subj2 F 26	Subj3 F 23	Subj4 M 23	Subj5 F 24	Subj6 M 30	Grp Aver Error
256	-730	-1237	-874	-776	-1236	-1029	-971
350	-725	-1239	-890	-770	-1232	-1023	-980
500	-729	-1243	-881	-758	-1234	-1024	-978
650	-724	-1237	-884	-771	-1231	-1022	-978
800	-733	-1245	-884	-763	-1239	-1024	-981
950	-731	-1237	-873	-772	-1241	-1021	-979
1100	-729	-1233	-873	-761	-1234	-1023	-976
1250	-727	-1237	-876	-771	-1236	-1022	-978
1400	-728	-1240	-875	-761	-1237	-1021	-977
1550	-732	-1240	-877	-769	-1242	-1021	-980
1700	-727	-1234	-881	-764	-1228	-1021	-976
1850	-724	-1242	-873	-761	-1241	-1026	-978
2000	-725	-1236	-875	-763	-1239	-1018	-976
2150	-730	-1236	-876	-767	-1237	-1020	-978
2300	-726	-1239	-873	-764	-1235	-1020	-
2450	-726	-1235	-878	-761	-1229	-1019	-975
2600	-731	-1233	-878	-762	-1236	-1024	-
2750	-738	-1235	-872	-762	-1235	-1024	-978
2900	-728	-1232	-880	-759	-1230	-1026	-976
3050	-725	-1233	-882	-764	-1249	-1028	-980
3200	-731	-1235	-877	-760	-1232	-1024	-976
3350	-724	-1239	-878	-761	-1239	-1019	-977
3500	-730	-1236	-867	-765	-1233	-1024	-975
Avg Err	-728	-1237	-877	-764	-1236	-1022	-978

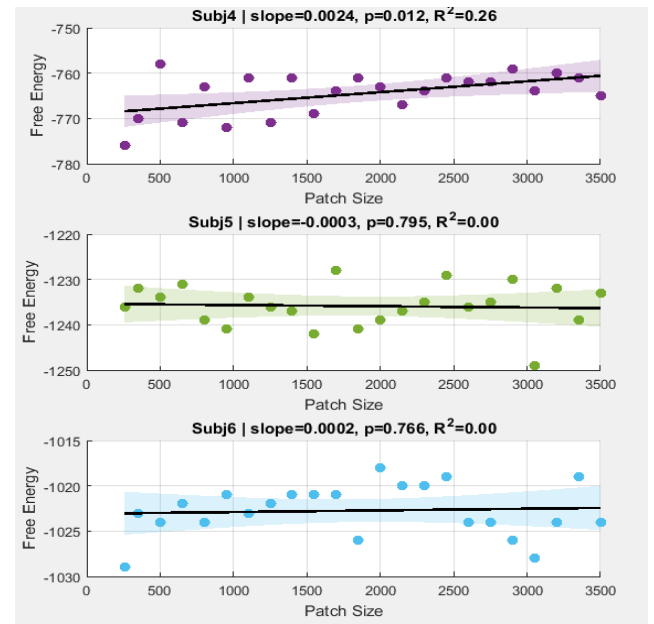


Fig. 17. Group Free Energy from MSP (Subj#1 to Subj#6)

In Fig. 17, the plots show Free Energy as a function of cortical patch size for six subjects. Each subplot presents the data points, linear regression line, and 95% confidence interval. Across all subjects, Free energy increases with increasing patch size, as indicated by the positive slopes of the regression lines. The shaded confidence intervals demonstrate the reliability of these trends. These results suggest that larger cortical patch numbers tend to yield higher Free energy, highlighting the influence of patch size on EEG source localization quality.

In Table 4, localization errors are calculated by varying the patches from 350 to 500 with increasing step of 150 using EEG MSP inversion, and the results are EEG source localization in the visual cortex. In Fig 18, red line represents group mean localization error (21.4 mm).

Table 4.

Localization Errors [mm] M: Male, F: Female

	Subj1 M 31	Subj2 F 26	Subj3 F 23	Subj4 M 23	Subj5 F 24	Subj 6 M 30	Avg Loc Err
MNI→	42, -42, -9	-38, -65, -13	20, -72, -14	41, -88, -8	50, -68, -8	41, -88, -8	
Patches							
350	6.6	0.0	44.3	22.9	16.1	26.9	19.5
500	6.6	67.6	28.4	21.3	7.6	22.6	25.7
650	5.2	15.8	21.6	34.3	15.1	15.1	17.9
800	5.2	11.2	38.3	47.1	14.2	24.1	23.4
950	6.4	13.8	19.3	47.8	13.4	26.9	21.3
1100	18.1	0.0	22.8	22.9	19	24.5	17.9
1250	6.6	15.7	17.0	39.6	6.7	23.7	18.2
1400	7.5	10.9	18.5	20.6	14.2	26.9	16.4

1550	6.0	4.1	17.2	9.1	12.2	26.9	12.6
1700	27.5	60.3	41.1	20.6	14.8	77.6	40.3
1850	4.0	0.0	38.3	5.0	13.4	7.5	11.4
2000	7.5	3.6	22.2	21.3	13.6	24.5	15.5
2150	38.7	0.0	42.6	9.1	13.6	24.5	21.4
2300	38.7	8.1	33.7	47.1	14.2	67.2	34.8
2450	38.7	0.0	17.2	11.8	6.7	24.5	16.5
2600	20.3	67.6	37.8	45.6	13.6	33.6	36.4
2750	7.5	7.0	38.6	20.6	15.1	26.3	19.2
2900	28.6	67.6	17.2	20.6	7.9	10.5	25.4
3050	27.6	8.1	50.6	20.6	13.4	15.7	22.7
3200	20.3	4.1	8.3	20.6	14.2	24.1	15.3
3350	17.1	6.1	17.4	20.6	13.6	24.5	16.6
3500	17.1	33.6	38.3	11.9	16.1	23.6	23.4
Mean	16.4	18.4	28.7	24.6	13.1	27.4	21.4

In Table 5, across six subjects, localization errors vary considerably, with mean errors ranging from 13.1 mm (Subj5) to 28.7 mm (Subj3), yielding a group mean of 21.4 mm. Variability is notable, as reflected by standard deviations from 3.2 mm (Subj5) to 19.5 mm (Subj2), while minimum errors show that certain patch sizes achieve very accurate localization (0–8.3 mm), and maximum errors indicate occasional large deviations (16.1–77.6 mm). Overall, the group mean provides a summary of typical performance, highlighting that careful selection of patch sizes can improve accuracy and reduce inter-subject variability

Table 5

Summary Statistics [mm] from Table 4

Metric	Subj1	Subj2	Subj3	Subj4	Subj5	Sub6	Group
Errors	M	F,	F	M	F	M	Mean
	31	2	23	23	24	30	Errors
Mean	16.4	18.4	28.7	24.6	13.1	27.4	21.4
Std Dev	9.3	19.5	11.7	13.3	3.2	18	12.5
Min	4	0	8.3	5	6.7	7.5	5.3
Max	38.7	67.6	50.6	47.8	16.1	77.6	50.7

The mean localization errors computed are plotted in Fig 18.

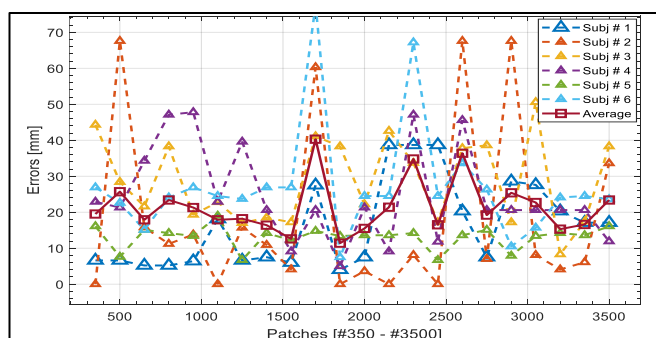


Fig. 18. Localization Errors

This practice estimates the trend of Subj#1, Subj#2, and Subj#5 are 16.4 mm, 18.4 mm, and 13.1 mm, respectively, which are lower than the group, mean localization error of 21.4 mm, indicating optimal localization accuracy and shown in the yellow boxes in the last row of the table. However, Subj#3 (female), Subj#4 (male), and Subj#6 (male) have higher localization errors of 28.7 mm, 24.6 mm, and 27.4 mm, respectively, exceeding group mean localization error of 21.4 mm and shown in red boxes in the last row.

4.3. Analysis of Optimized Localization Errors

Table 6 presents the localization errors for individual subjects, along with an average localization error reduced to 4.1 mm. This improvement is achieved using the average optimized MNI spaces obtained through the MSP inversion approach. With the reduction in localization errors, brain active sources can be further optimized and localized. These localization errors, with a mean value of 4.1 mm, represent a significant improvement.

Table 6.

Optimized Localization Errors [mm]

Subj1	Subj2	Subj3	Subj4	Subj5	Subj6	Avg
M	F	F	M	F	M	Loc
31	26	23	23	24	30	Errors
42,	-39,	[37	[37,	[44,	[48,	
-43,	-66,	,-69,	-69,	-80,	-68,	
-22	-13	-14]	-15	-7]	2]	
5.5	1	17.5	4.4	4.2	3.2	6.0
5.5	1	25.4	4.2	4.1	1.7	7.0
3	10.3	6.3	4.4	4.2	3.6	5.3
3	4	6.3	0	4.1	1.7	3.2
6.6	1	4.6	0	1	1.7	2.5
5.5	3.2	2.2	4.2	1	1.7	3.0
6.8	1	6.7	0	4.2	6	4.1
5.1	1	2.2	0	1	11.8	3.5
1.4	6.8	2.2	0	4.1	3.2	3.0
7.3	4	6.4	0	4.2	1.7	3.9
7.3	6.2	3.2	0	1	3.7	3.6
5.3	3.6	7.5	1.6	3.0	3.6	4.1

In Table 7, across six subjects, mean localization errors range from 1.2 mm to 7.7 mm, with a group average of 4.0 mm, indicating generally accurate EEG source localization. Variability is moderate (group SD 3.3 mm), though some subjects (e.g., Subj3) show higher errors and inconsistency. Overall, optimal patch sizes can achieve low errors, while extreme patch sizes may increase localization uncertainty.

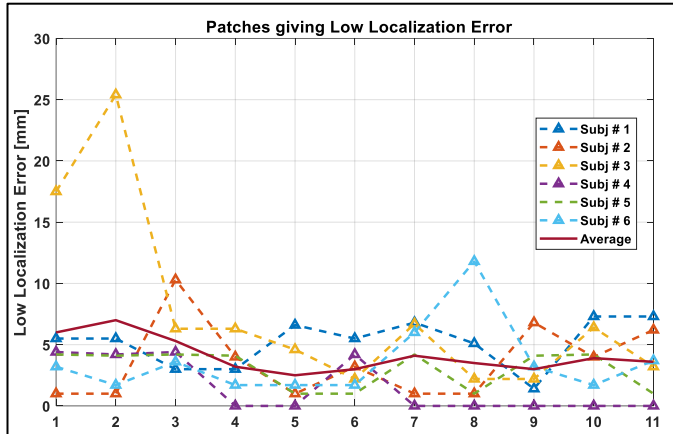
Table 7

Summary Statistics [mm]

Metric	Subj1 M 31	Subj2 F 2	Subj3 F 23	Subj4 M 23	Subj5 F 24	Subj6 M 30	Group Mean
Mean Error	5.3	3.2	7.7	1.2	2.8	3.6	4
Std Dev	1.9	2.7	6.7	1.9	1.5	2.7	3.3
Min Error	1.4	1	2.2	0	1	1.7	1.2
Max Error	7.3	10.3	25.4	4.4	4.2	11.8	10.6

In Fig. 19, seven lines of localization errors are plotted, with each line representing an individual subject. The red line represents the average localization error obtained using the default patches. This red line indicates a localization error below the mean value of 4.1 mm, which is significantly reduced. It is observed that Subj1 (male), Subj2 (female), and Subj3 (female) are above the average line (i.e., the red line above 5 mm) and indicated in yellow box, resulting in higher localization errors. In contrast, Subj#4 (male), Subj#5 (female), and Subj#6 (male) are below the average line (i.e., the red line below 5 mm), indicating lower localization errors and shown in red box.

This analysis confirms that optimized patches contribute to improved source localization accuracy for most subjects.

**Fig. 19.** Group Analysis of Loc errors

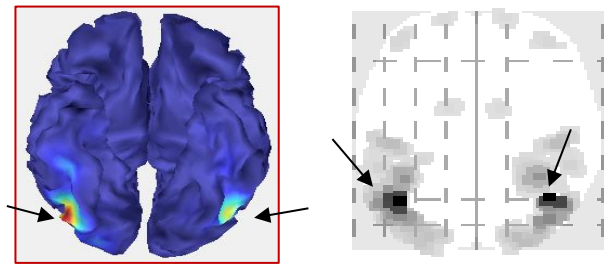
Further, based on the EEG source localization results, optimized MNI coordinates and high free energy and low localization errors, multiple regions of the brain were identified as active during visual stimulation.

Fig. 20, shows the brain areas activated during visual stimulation, based on EEG source localization. The left panel displays a 3D cortical surface of the brain with highlighted regions (in yellow-red), indicating active sources. The arrows point toward regions of significant activation. The right panel is a 2D projection showing the spatial distribution of

activity, helping to confirm the locations in a flattened top-down view.

From the results, it is demonstrated that, the most significant activation was observed in the right fusiform gyrus (BA 37), which is known for its role in facial and object recognition. Additional activity was localized in the visual association cortex (BA 19), the secondary visual cortex (BA 18), and the inferior temporal gyrus (BA 20), all of which are associated with various levels of visual processing.

Fig.20. confirms that multiple visual-related areas in the brain are actively involved during visual stimulation, with strong bilateral activation especially in the right fusiform gyrus, as shown by the coloured activity zones.

**Fig. 20.** Right Fusiform (37), visual association cortex (19), secondary visual cortex (18), and inferior temporal gyrus (20), where brain sources are active for visual stimulation.

5. Conclusion

This research of EEG source localization was conducted across six (06) subjects using a proposed MSP inversion algorithm across cortical patch ranges (350 to 3500, step size 150).

As in Table 4, across all patches, the localization error ranges across subjects varied between 13.1–28.7 mm. The findings confirm that the MSP-based approach provides reliable and accurate source localization in the visual cortex. As in Table 7, across individual subjects with selected patches, mean errors range from 1.2 mm (Subj#4) to 7.7 mm (Subj#3). The group mean is 4.0 mm, indicating that, on average, EEG source localization is reasonably accurate across the six subjects.

The analysis revealed that optimized free energy values correspond to low localization errors, with a group average of 4.1 mm. Individual subject errors largely fell within the favourable range of 1–5 mm, demonstrating the effectiveness of the method.

Key active brain sources were consistently localized in regions associated with visual and face processing, including the right fusiform gyrus (BA 37), visual association cortex (BA 19), secondary visual cortex (BA 18), and inferior temporal gyrus

(BA 20). These regions were robustly engaged during visual stimulation, contributing significantly to the recorded scalp voltages.

This method holds strong potential for advancing non-invasive brain mapping and improving applications in cognitive neuroscience and clinical diagnostics. Further, the proposed approach can be applied to the development of brain-computer interfaces (BCIs), neuro-feedback systems, and intelligent human-machine interaction frameworks. Enhanced localization accuracy can significantly improve signal interpretation in real-time neural decoding systems, wearable neurotechnology, and assistive communication devices. MSP based EEG source localization improves the accuracy and interpretability of cortical mapping with potential applications in brain computer interface and human machine interface and assistive systems. Additionally, this work can contribute to the design of neuroimaging tools and algorithms used in embedded systems for medical and rehabilitative applications.

6. Future Research

Multiple Sparse based EEG source localization is a powerful brain mapping techniques that identifies precise neural activity sources, making it crucial for advancing brain computer interfaces for controlling devices with computer accuracy, personalized targeted neuro therapies, and early disease detection through identifying abnormal brain activity sources. My future research work would be on the said improving and integrating techniques.

7. Acknowledgment

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