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SCIENTIFIC PAPER

# EEG based brain source localization comparison of sLORETA and eLORETA

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**Abstract** Human brain generates electromagnetic signals during certain activation inside the brain. The localization of the active sources which are responsible for such activation is termed as brain source localization. This process of source estimation with the help of EEG which is also known as EEG inverse problem is helpful to understand physiological, pathological, mental, functional abnormalities and cognitive behaviour of the brain. This understanding leads for the specification for diagnoses of various brain disorders such as epilepsy and tumour. Different approaches are devised to exactly localize the active sources with minimum localization error, less complexity and more validation which include minimum norm, low resolution brain electromagnetic tomography (LORETA), standardized LORETA, exact LORETA, Multiple Signal classifier, focal under determined system solution etc. This paper discusses and compares the ability of localizing the sources for two low resolution methods i.e., sLORETA and eLORETA respectively. The ERP data with visual stimulus is used for comparison at four different time instants for both methods (sLORETA and eLORETA) and then corresponding activation in terms of scalp map, slice view and cortex map is discussed.

**Keywords** Electroencephalography · Inverse problem · sLORETA · eLORETA · Localization error

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## Introduction

Electroencephalography (EEG) is the non-invasive/invasive functional neuroimaging technique developed to measure brain activity by measuring electrical signals generated with the help of electrodes placed on the scalp [1–4]. This EEG signal is not pure in form; rather it has different contaminations. These contaminations are subjected to certain artefact removal techniques to make it possible for further processing for various EEG applications [5–7].The estimation of the sources responsible for electromagnetic activity inside the brain based on the potential recorded through the electrodes is one of major applications of EEG. This problem is termed as EEG source localization or EEG inverse problem as the model is estimated with the available data set [8].

The brain source localization problem is divided into forward problem and inverse problem. In the forward problem, the data parameters (electric potential in the case of EEG) are extracted from the model. For the forward problem solution, various head modelling schemes are proposed which are based upon analytical and numerical head modelling. For the numerical head modelling, finite element method (FEM), boundary element method (BEM), finite volume method (FVM) and finite difference method (FDM) is proposed [9]. However, inverse problem goes for the estimation of the model from data parameters. Hence, EEG inverse problem is an underdetermined ill-posed inverse problem. This is because the number of unknown parameters (active sources) is greater than number of known parameters (electrodes used) [10].

There exist two general approaches for the localization as proposed by researchers. Either the signals are assumed to be generated by a small number of focal sources. This

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approach is called as equivalent current dipole (ECD). However, if all possible source locations are assumed simultaneously, then it is known as Linear distributed approach [11].

Several methods are developed for the solution of EEG inverse problem keeping in mind low localization error, low computational complexity and validation of the achieved results. Among them, most popular methods are minimum norm method (MN) [12], low resolution brain electromagnetic tomography (LORETA), standardized LORETA, exact LORETA, Multiple Signal classifier (MUSIC) and Recursively applied and projected MUSIC (RAP MUSIC) [13, 14], focal under determined system solution (FOCUSS) [15], weighted minimum norm-LORETA (WMN-LORETA) [16], recursive sLORETA-FOCUSS [17], standardised shrinking LORETA-FOCUSS [18] etc. However, this paper discusses sLORETA and eLORETA in detail with results obtained for each method for a set of data.

This source modeling with the help of EEG is useful for many neuroscience, cognitive, behavioral science applications. These applications include diagnoses of various brain disorders (epilepsy, depression, stress, sleep disorders etc.). The studies used for brain source localization are used for surgical purposes in hospitals such as for non-invasive localization of epileptogenic zones which provides surgical help for epileptic patients [19].

"Methods" section discusses sLORETA and eLORETA in detail with their mathematical relationship; "Methodology" section is dedicated for methodology. "Results and discussion" section presents the results and discussion. "Conclusion" section produces the conclusion.

## Methods

### Standardized LORETA

This technique is advanced version of LORETA which is low resolution distributed imaging technique for brain source localization. This technique is based upon computation of current distribution throughout full brain volume [8]. LORETA provides smooth and better localization for deep sources with less localization errors but with low spatial resolution and blurred localized images of a point source with dispersion in the image. The low spatial resolution of LORETA is undesirable in some cases such as feature extraction of spatio-temporal pattern recognition where high resolution is needed. Since the development of LORETA as low resolution localization technique, many methods are developed. These methods include sLORETA, eLORETA, WMN-LORETA etc. The standardized LORETA also known as sLORETA is based upon the assumption of the standardization of the current density which implies that not only the variance of the noise in the EEG measurements is taken into account but also the biological variance in the actual signal is considered [20]. This biological variance is taken as independent as uniformly distributed across the brain resulting in a linear imaging localization technique having exact, zero-localization error. This localization technique has got resemblance to the method provided by Dale et al. in which the localization is provided on a standardization of the estimates of current density. However, unlike the [21], sLORETA takes into account both variations which are variations due to actual sources and variation due to noisy measurements if they exist.

The current density estimates are given by MN method as in Dale with the localization inference based on standardized values of the current density estimates. The way standardization for sLORETA is performed is different from Dale's method resulting in zero-localization for the sLORETA.

The mathematical formulation for the sLORETA is given as under:

$$F = \|\varphi - KJ - c1\|^2 + \alpha\|J\| \tag{1}$$

where $\varphi$ = electrical potentials measured from scalp with the help of electrodes, $K$ is lead field matrix, $J$ is current density, $\alpha \geq 0$ is regularization parameter and $c1$ is constant. This functional has to be minimized with respect to $J$ and $c1$, for given $K$, $\varphi$ and$\alpha$. By using average reference transforms of $\varphi$ and $K$, the above equation can be rewritten as:

$$F = \|\varphi - KJ\|^2 + \alpha\|J\| \tag{2}$$

With minimum $\hat{J} = T\varphi$ where, $T = K^T[KK^T + \alpha H]^+$. Therefore, for the standardised estimates of current density, the variance of estimated value of $\hat{J}$ is to be calculated. So the electric potential variance $S_\varphi \in \Re^{N_E \times N_E}$ can be explained as:

$$S_\varphi = KS_J K^T + S_\varphi^{Noise} = KK^T + \alpha H \tag{3}$$

From the above equation, the variance for the estimated current density can be given:

$$S_{\hat{J}} = TS_\varphi T^T = T\left(KK^T + \alpha H\right)T^T = K^T\left[KK^T + \alpha H\right]^+ K \tag{4}$$

The sLORETA linear imaging method is:

$$\sigma_v = \left[S_{\hat{J}}\right]_v^{-\frac{1}{2}} \hat{j}_v \tag{5}$$

where $[S_{J^\wedge}]_v \in \Re^{3\times 3}$ is the $v$th $3 \times 3$ diagonal matrix in $S_J$ and $\left[S_{\hat{J}}\right]_v^{-\frac{1}{2}}$ is the symmetric square root inverse. The

squared norm of $\sigma_v$ corresponds to the estimate of standardised current density power as:

$$\sigma_v^T \sigma_v = j_v^T [S_{J^\wedge}]_v^{-1} \overset{\wedge}{j}_v \tag{6}$$

The simulations are carried out by using Talairach human brain atlas. A total of 6,430 voxels at 5 mm spatial resolution were produced under these constraints. For each dipole, there exist three unknown values making the number of unknowns as $3 \times 6{,}430 = 19{,}290$ with 25 electrodes. Different localization methods are compared with sLORETA which include MN and proposed by [21] in terms of localization errors and spatial spread. The simulations with noise and without noise demonstrate that sLORETA has far better quality with exact localization and zero-error localization as compared with MN and Dale methods which shows that the sLORETA is perfect first order localization technique. The low resolution offered by sLORETA is its limitation factor as compared to modern spectral subspace based estimation techniques with high resolution. Hence, the low resolution imaging results in weak performance for recovering of multiple sources when the point-spread functions of sources overlap. Also, the imparting of regularization functions for stability in inverse problem causes spatial blurring in sLORETA and LORETA techniques which is undesirable feature in pattern recognition.

eLORETA

There have been many useful attempts to minimize the localization error by choosing the weight matrix in a more adequate way. However, there exists one methodology to give more importance to the deeper sources with reduced localization error. The study carried out in [22] shows this method by achieving depth weighting with reduced localization error from 12 to 7 mm. This method was developed and recorded as working project in the University of Zurich in March 2005 [20]. According to [22], eLORETA is a genuine inverse solution which provides exact localization with zero error in the presence of measurement and structured biological noise. Hence the family of linear imaging methods are parameterized by a symmetric matrix $C \in \Re^{N_E \times N_E}$, such that,

$$\overset{\wedge}{j}_i = \left[ \left( K_i^T C K_i \right)^{-1/2} K_i^T C \right] \varphi \tag{7}$$

where $\overset{\wedge}{j}_i \in \Re^{3\times 1}$ is an estimator for calculation of neuronal activity at the $i$th voxel. In this research [19], the localization ability of a linear imaging method is elaborated by considering the actual source as an arbitrary point test source at $j$th voxel which assumes that:

$$\varphi = K_j A \tag{8}$$

where $K_j$ is lead field matrix and $A \in \Re^{3\times 1}$ is a vector which contains dipole moments for the sources. By making use of above equations, one can write for the estimation values as:

$$\left\| \overset{\wedge}{j}_i \right\|^2 = A^T K_j^T C K_i \left( K_i^T C K_i \right)^+ K_i^T C K_j A \tag{9}$$

Now, considering the case of eLORETA, the current density estimator at the $i$th voxel can be written as:

$$\overset{\wedge}{j}_i = W_i^{-1} K_i^T \left( K W^{-1} K^T + \alpha H \right)^+ \varphi \tag{10}$$

Upon comparison of the equations given above, one can deduce that the exact, zero error localization can be achieved with weights satisfying the equation given below:

$$W_i = \left[ K_i^T \left( K W^{-1} K^T + \alpha H \right)^+ K_i \right]^{1/2} \tag{11}$$

The eLORETA method is standardised which implies that it's theoretical expected variance is unity. eLORETA suffers from the disadvantage of low resolution like other members of LORETA family. Due to low resolution, undesired blurring is caused in resultant localization images when the space is subjected to regularization for EEG inverse problem.

After discussing in detail with mathematical background for sLORETA and eLORETA, the discussion for applied methodology is presented below.

## Methodology

The comparison between sLORETA and eLORETA is carried out by using utilities available with sLORETA software. This software package is developed by The KEY Institute of Brain-Mind Research, University Hospital of Psychiatry, Zurich, Switzerland [20, 23].

The ERP data for comparison is taken from sLORETA software which is provided by Dr. Michaela Esslen, Institute of Neuropsychology, University of Zurich, Zurich, Switzerland. According to the details of the data provided at [23], the data has following specifications: it is visual ERP data which shows that the data is taken by giving visual stimulus to participants which in this case is pictures of flowers. The data is sampled at 256 Hz with electrode names stored in a file list25e.txt. Total number of participants is 17 with ten females and seven males. The data is grouped into paired and non-paired. For paired ERP data, two visual stimuli (stimulation with pictures of flowers and stimulation with grey screen) are provided to participants. However, with ERP non-paired data only one visual stimulus (pictures of flower) is provided. The number of

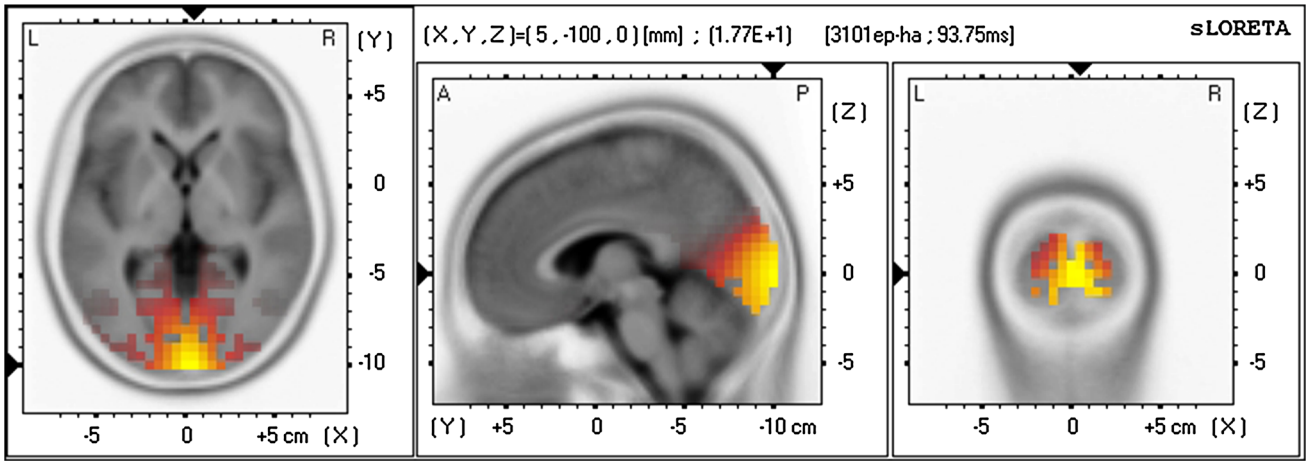


**Fig. 1** Activation map for sLORETA (93.75 ms)

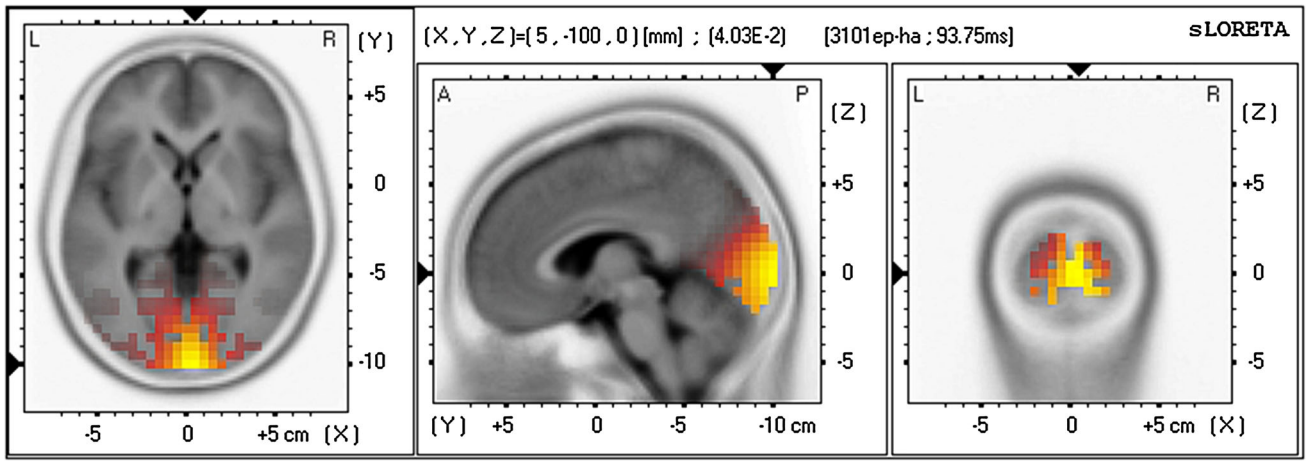


**Fig. 2** Activation map for eLORETA (93.75 ms)

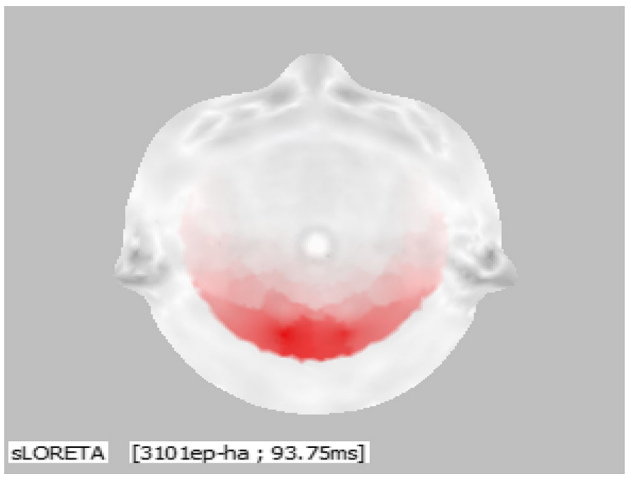


**Fig. 3** Scalp map for sLORETA

electrode taken is 25 with sampling rate selected as 256 Hz. The first step is the conversion of text file of electrodes into Talairach electrodes coordinates i.e., from .txt to .sxyz extension. Next step is creation of transformation matrix from .sxyz file. It can be sLORETA or eLORETA transformation depending upon application. After necessary transformation, the file is loaded into viewer/explorer utility of sLORETA software. Then, the ERP paired data from the data set file is selected. The selected data is checked for different time instants to visualize the activation in Slice viewer, Scalp map and 3D cortex map respectively. For this study, the time instants are marked for 93.75, 253.906, 480.469 and 42.968 ms. The activation is checked and compared for sLORETA and eLORETA for all above mentioned time instants. The corresponding results are shown in terms of regions activated with

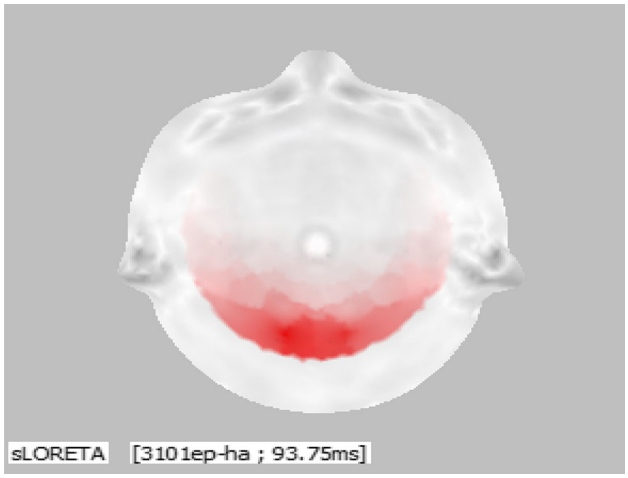


**Fig. 4** Scalp map for eLORETA

corresponding maps. The analysis for both methods i.e., sLORETA and eLORETA is carried out with same software package and it generates results for both. The results are inspected in visual terms only. However, it should be noted that proper captions are provided for each method.

## Results and discussion

The results are taken by following the methodology stated above. According to results, activation was observed for different brain regions for 4-time instants. The activation is dependent upon the stimulus given and the attention kept by the subject during the experimentation. At the time 93.75 ms, the most activated region was occipital for sLORETA and eLORETA method as shown in Figs. 1

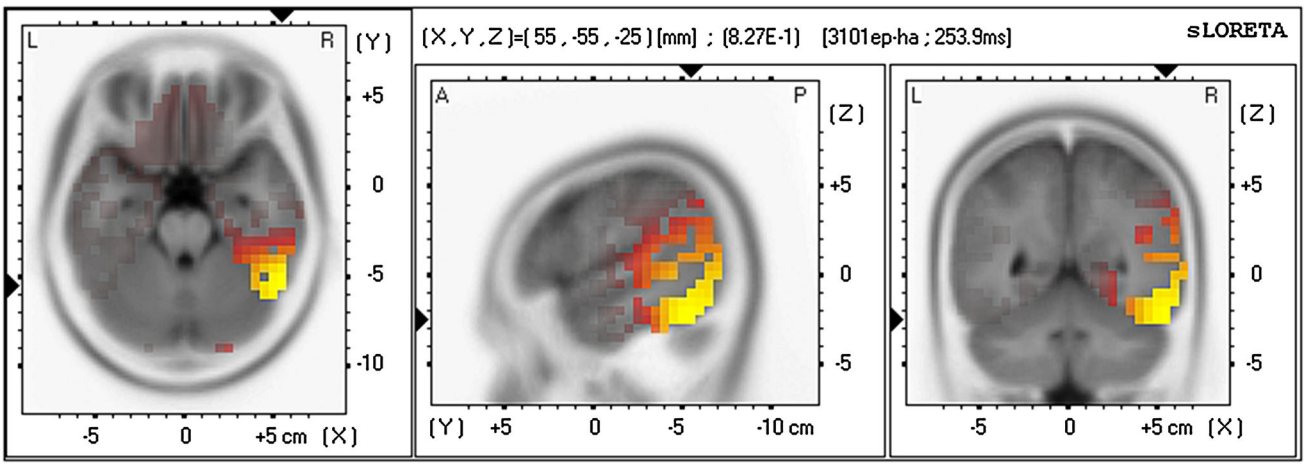


**Fig. 5** Activation map for sLORETA (253.906 ms)

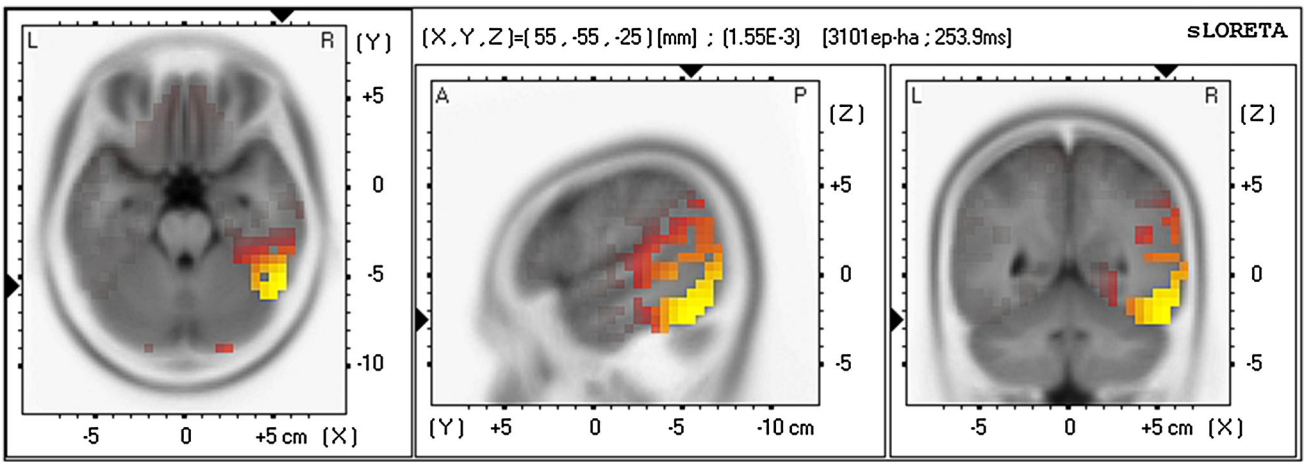


**Fig. 6** Activation map for eLORETA (253.906 ms)

and 2 respectively. However, upon visual inspection, it is evident that activation results produced by sLORETA are blurred as compared to eLORETA. eLORETA produces clear and finest details of activation region which in this case is occipital as compared to sLORETA. This same fact is valid for 3D scalp results as are produced in Figs. 3 and 4 for sLORETA and eLORETA respectively. For the second time instant i.e., 253.906 ms, it was observed that the active region for both inverse methods is temporal region. As seen in Figs. 5 and 6, it is clear that eLORETA produces more accurate localization of most active sources by suppressing blur activations. However, sLORETA has though localize the active region but with less accuracy as compared to eLORETA. The scalp map which is shown for sLORETA and eLORETA in Figs. 7 and 8 suggests that eLORETA has clearer view as compared to sLORETA. The third time instant was taken at 480.46 ms for both inverse methods. The corresponding activation maps are produced in Figs. 9 and 10 respectively. The most active region for this case is parietal region. The eLORETA has produced results with more accuracy and exact localization by removing less significant activation and thereby decreasing localization error. However, sLORETA produced distributed imaging (Fig. 9) but with some non-significant sources with less intensities. The eLORETA produced results for the same data set with only significant and high intensity sources. The low intensity sources are suppressed (Fig. 10), which improves the overall quality for localization of sources. This feature of reduced localization error is desirable for pattern recognition application of source localization. The scalp maps for this time instant are produced in Figs. 11 and 12 respectively. The time instant 42.968 ms shows activation in frontal region for both sLORETA and eLORETA respectively. The results are shown in Figs. 13 and 14 for sLORETA and eLORETA. The results show much clear activation for eLORETA as compared to

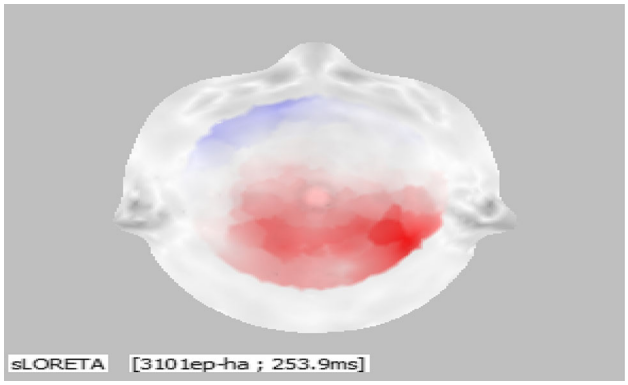


**Fig. 7** Scalp map for sLORETA (253.9 ms)

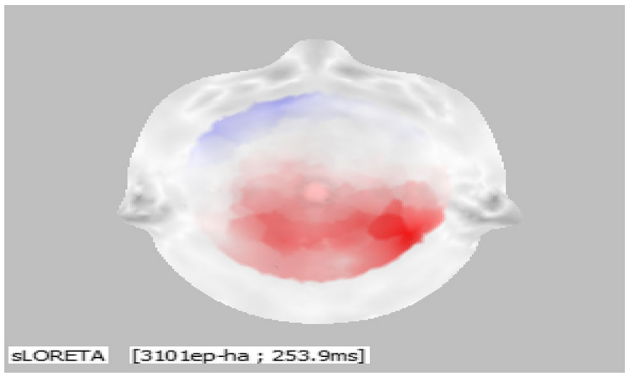


**Fig. 8** Scalp map for eLORETA (253.9 ms)

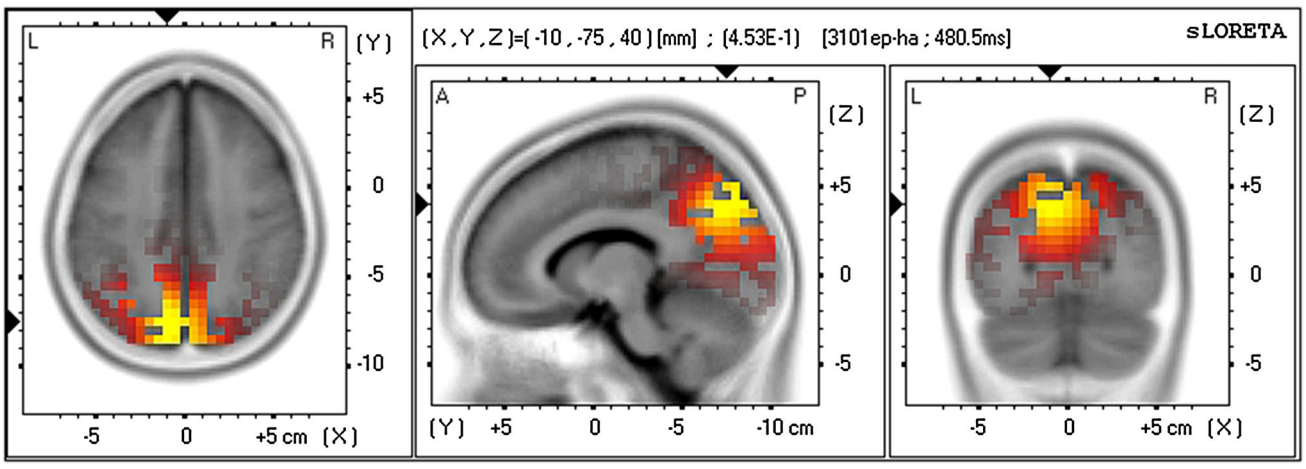


**Fig. 9** Activation map for sLORETA (480.5 ms)

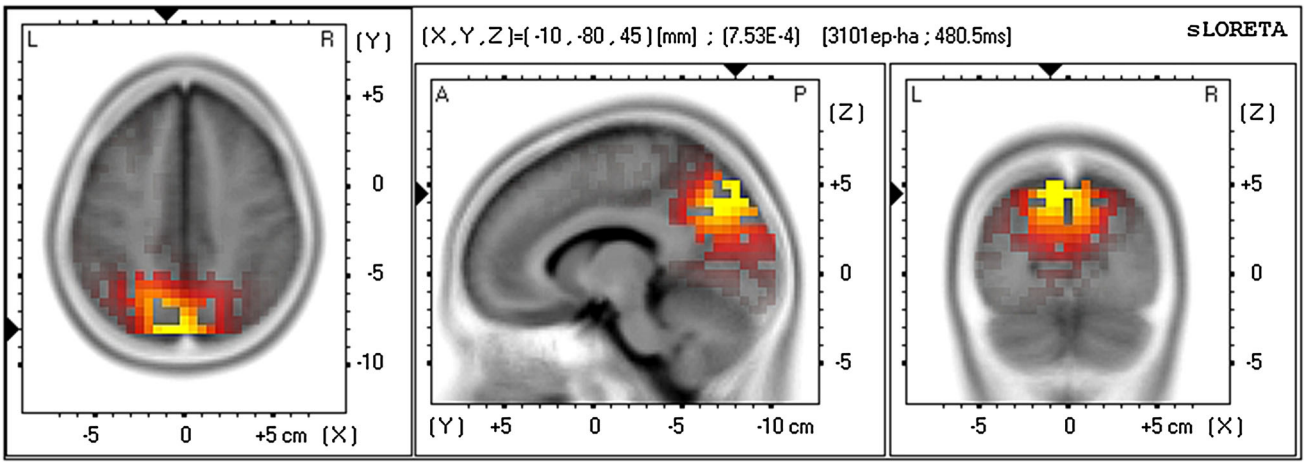


**Fig. 10** Activation map for eLORETA (480.5 ms)

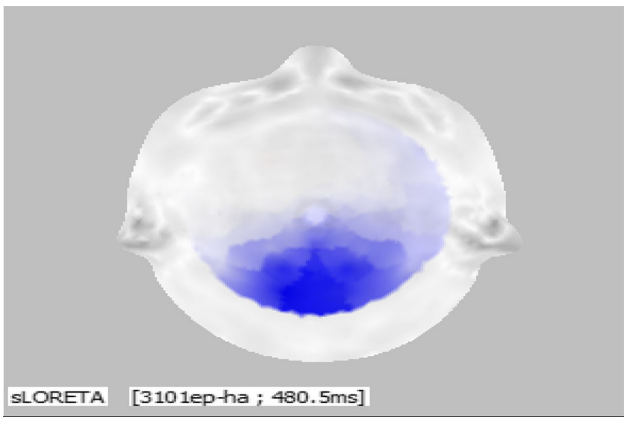


**Fig. 11** Scalp map for sLORETA (480.5 ms)

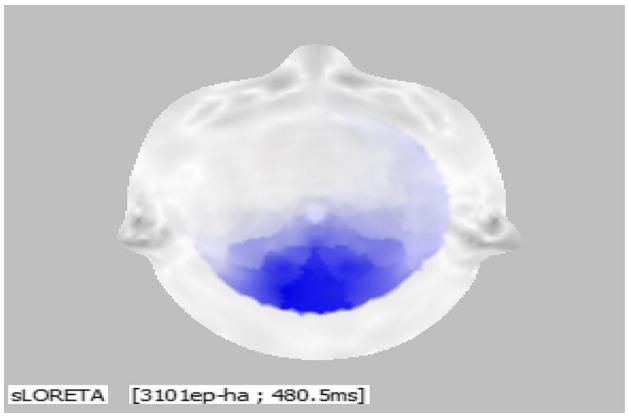


**Fig. 12** Scalp map for eLORETA (480.5 ms)

sLORETA. Same comment is held valid for the scalp map shown in Figs. 15 and 16 for both methods. From the above discussion and the results for both methods, it is evident that eLORETA provides localization results in a more accurate fashion with less localization error and clear visibility. However, though sLORETA provides the activation maps showing activation in same regions as with eLORETA but lags in terms of resolution and localization error. Therefore, eLORETA can be considered best choice for localizing activated sources inside the brain with the help of EEG/ERP data as compared with other low resolution localizing algorithms such as LORETA and sLORETA.

## Conclusion

In this paper, a comparative study was carried out for two EEG source localization algorithms i.e., sLORETA and eLORETA. The results were developed by using sLORETA software provided by The KEY Institute of Brain-Mind Research, University Hospital of Psychiatry, Switzerland with the ERP data taken from 17 subjects with visual stimulus provided at the time of experimentation. The comparison was made by checking out the localization ability for both algorithms by means of visual inspection through activation and scalp maps. The comparison showed that eLORETA performs in a better way for localizing the sources with clear and less blur quality of images as compared to sLORETA. Also, the ability of suppressing less significant sources is higher for eLORETA as compared to sLORETA. Hence, it is concluded that for EEG/ERP data with any mental task (for example visual stimulus, auditory stimulus etc.), eLORETA performs well in terms of less localization error and visibility as compared to other low resolution techniques (LORETA and sLORETA). Also the ability of eLORETA to suppress the non-significant details in the resultant localization is

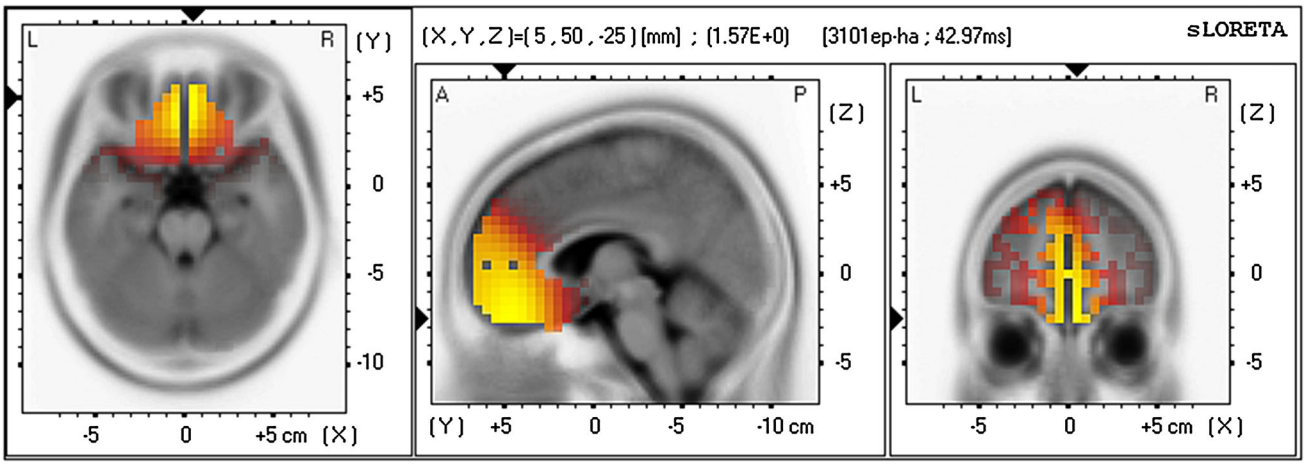


**Fig. 13** Activation map for sLORETA (42.6 ms)

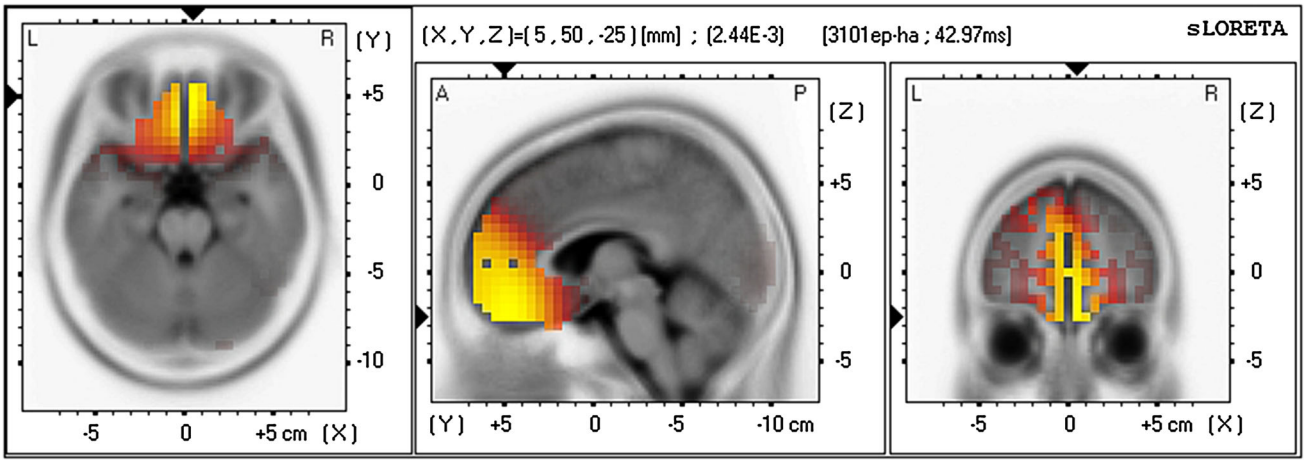


**Fig. 14** Activation map for eLORETA (42.6 ms)

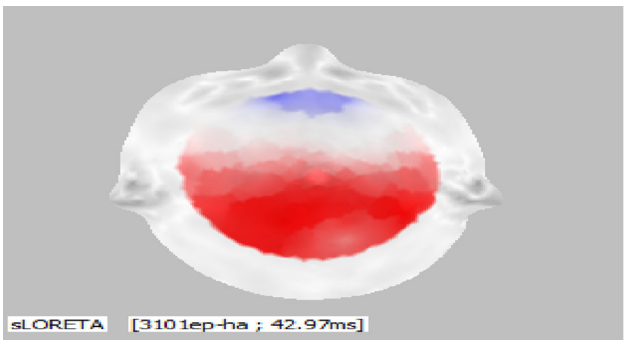


**Fig. 15** Scalp map for sLORETA (42.97 ms)

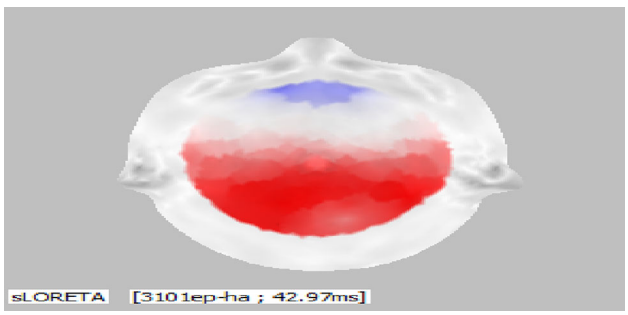


**Fig. 16** Scalp map for eLORETA (42.97 ms)

efficient as compared with sLORETA. This study is focused on low resolution source imaging of brain sources by using EEG signals. Therefore, this study is clinically useful for initial diagnoses the properties of cerebral neural networks in cognitive, behavioral and neuroscience applications. Such applications include the localization of epileptic foci for the patients suffering from epilepsy. However, the localization of sources in certain frequency bands is also applicable with such study for psychiatry and psychopharmacological application in hospitals. For clinical surgery applications, this study is equally applicable and valid such as for non-invasive localization of epileptogenic zones in patients with partial seizures. Apart from

this, it can also be used for pathological applications related to sleep disorders, depression, stress and fusion techniques. Though the high resolution subspace based approaches (MUSIC, RAP-MUSIC, Root MUSIC etc.) by using dipole approach can provide results with higher accuracy and low localization error; however, as an initial diagnoses tool based upon visual inspection and statistical analysis for clinical purposes, this study can be used for localization of brain tumour and working memory identification purposes.

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