

# INTERACTION BETWEEN NOISE AND LESION MODELING ERRORS ON EEG SOURCE LOCALIZATION ACCURACY

P. Bruno<sup>1,2</sup>, F. Vatta<sup>1</sup>, P. Inchingolo<sup>1</sup>

<sup>1</sup>D.E.E.I., University of Trieste, Trieste, Italy

<sup>2</sup>Department of Psychology, University of Trieste, Trieste, Italy

**Abstract-** EEG dipole source reconstruction requires the assumption of a source model and of a conductive head model. Head-modeling errors and measurement noise in the EEG induce localization errors in the results of EEG source analysis. In this study effects of brain lesions on EEG dipole source localization have been investigated by computer simulation. We present a sensitivity study quantifying the effect on source localization accuracy of the interaction between the uncertainty in lesion conductivity assignment (LCA) and various levels of signal to noise ratio (SNR) in the EEGs. An inverse dipole fitting procedure, based on simulated noiseless EEG measurements and with SNR 5, 10 and 15, was carried out in 5 pathological situations, assuming an incorrect LCA ranging from a half to twice the real value. Incorrect LCA in noiseless conditions led to markedly wrong source reconstruction for high lesion conductivity values (localization errors up to 1,7 cm). We propose a method based on residual error analysis to improve lesion conductivity estimate. This procedure can identify lesion tissue conductivity with only a few percent error reducing the LE to values given by noise only.

**Keywords** – Electroencephalography, noise, lesion, source localization, dipole source, conductivity.

## I. INTRODUCTION

Dipole source localization using scalp recorded EEG is used to estimate the location of sources of electrical activity in the brain. EEG source localization estimate requires the assumption of proper models of the EEG source and of the head volume conductor. The accuracy with which a source can be located is affected by a number of factors including head-modeling errors and EEG noise. Besides geometrical head modeling errors, the large uncertainty in determining most of the conductivity values of the head model compartments is one of the major factors that influences the accuracy of EEG source localization estimate. In fact, the in-vivo conductivity values would be needed but unfortunately they are not measurable in living patient without surgery and they must therefore be obtained from the wide range of values reported in the literature. So far, many authors have studied the effects on the EEG source-localization accuracy of geometrical and conductivity (electrical parameters of the model) in normal conditions (i.e. in absence of morphologic deviations from normal heads), and only a minor attention has been devoted to estimate source localization accuracy in presence of a brain lesion. Brain lesions can present conductivity values dramatically different from those of surrounding normal tissues. Lesions create eccentric conductive inhomogeneities in the head volume conductor which have to be included in head models for accurate neural source reconstruction [1]. The uncertainty in determining tissue conductivity values is particularly large for brain lesions, because of the poor statistics available [2]: brain

lesion conductivity values range from 0.52 to 1.89 S/m for a liquid lesion, and from 0.0018 to 0.0070 S/m for a calcified lesion. In a previous work [3] we performed a sensitivity study of the effects of lesion conductivity mispecification on the EEG dipole localization accuracy in presence of brain lesions. We found that Lesion Conductivity Assignment (LCA) errors determine source localization errors. For almost calcified lesions their parametric definition (i.e. LCA) can be done approximately without incurring in remarkable localization errors. Conversely, the parametric setting for liquid-filled lesions must be accurate to avoid incurring large source localization errors (up to 17 mm). In the same study we proposed also a error reduction method (line intersection technique - LIT) which allows to reduce the uncertainty in determining lesion conductivity and therefore to reduce dipole source localization error. Noise contributes to errors in dipole source localization [4]. Noisy potential distributions can be generated by adding white noise to a noiseless potential distribution. Solving the inverse problem yields dipole coordinates which deviate from those found in the noiseless case. Additive noise with zero mean generates deviations in the dipole coordinates also with zero mean hence noise can not generate a systematic dipole location error but rather a random location error [5].

In this study we check the LIT method for error reduction adding noise to EEG data. We adopted a modified spherical model of the head (eccentric-spheres model) valid also in pathological conditions. Although spherical head models are only an approximation to an actual head, the benefit arising from simplified calculations justifies their use in many situations. Since our aim was to evaluate the effect of lesion conductivity mispecification on dipole source localization, we could neglect the peculiar errors due to a spherical approach versus a realistic one, simply comparing simulation results collected with spherical models in different situations.

We show here the combined effect of noise and LCA error on source reconstruction accuracy and show that, even a rough implementation of LIT can reduce localization error (LE) to the level imposed by the quality of the recording, i.e. to the accuracy determined by EEG noise.

## II. METHODOLOGY

To investigate the effects of interaction between EEG noise and lesion conductivity mispecification on source localization accuracy we simulated many noisy EEG scalp-potential distributions (which we will refer to as the “measured potentials”) in presence of a brain lesion.

A pathological head model was used to simulate many EEG scalp-potential distributions in presence of a brain lesion. A model consisting of four eccentric spheres was used to give a mathematical description of the head as a volume conductor (Fig. 1). Our model consisted of three large

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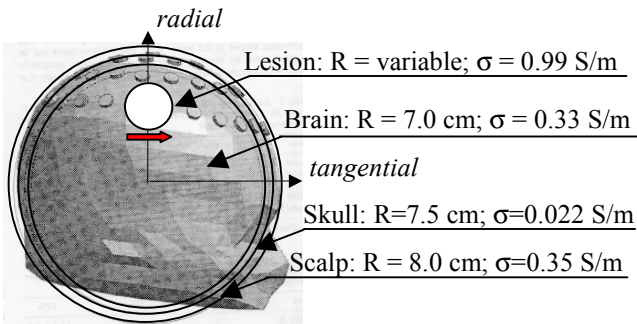


Fig. 1. Pathological head model: (R) radius and ( $\sigma$ ) conductivity of model compartments.

concentric spheres (3 compartments) and of an eccentric spherical “bubble” (lesion compartment). The concentric layers have different electrical conductivities and represent scalp, skull and brain; values of the radii for the brain, the skull and the scalp have been kept constant. The lesion is represented by the eccentric spherical “bubble” with altered conductivity in the brain region. Radius, conductivity (electrical property) and position of the bubble (distance of its center from the center of the head) can be varied according to the simulated pathology. The adopted tissue conductivity values for scalp, skull and brain are shown in Fig. 1; they will be referred to as “baseline conductivity values” and were assigned after reviewing the literature [6]. We considered a brain within which a fluid lesion was present and assigned the bubble a conductivity of three times that of the surrounding normal brain tissue ( $\sigma_{\text{lesion}}/\sigma_{\text{brain}} = 3$ ) to represent a liquid filled lesion. The single current-dipole source model was adopted to approximate the neural electric source in the brain (see Fig. 1). We test 5 different conditions for lesion dimension and relative position of neural source and lesion shown in Table 1. Dipole amplitude has been kept constant through all simulations (50  $\mu\text{A}\cdot\text{m}$ ).

This study has been conducted using the following procedure. First, the potential at the electrode positions was simulated in all the above-described situations adopting baseline conductivities for all the tissues (see Fig. 1) using previously developed mathematical methods for the analytic calculation of the EEG potentials [7]. The noisy EEGs were obtained adding Gaussian noise with zero mean and unitary standard deviation to forward calculated electrode scalp potentials. The noise was uncorrelated between the electrodes. The signal-to-noise ratio (SNR) was defined as the ratio between signal and noise powers. The procedure was repeated for SNR 5, 10 and 15. An equivalent dipole-source for the given (simulated) EEG distribution was then calculated (the inverse bioelectric problem solution) in absence of noise and for the 3 different levels of SNR considered. This was achieved by means of a least-squares fit between the measured potentials and the potential distribution calculated using the head model with a lesion conductivity assignment error. In other words, for each of the analyzed 4 noise situations, the inverse problem solution was carried out having assumed a wrong conductivity for the lesion with all the other parameters unchanged. We repeated this procedure for several values of lesion conductivity misassignment and spanned conductivity from half (-50%) to twice (+100%) of baseline value by 10% baseline conductivity steps, totaling 16 cases for each of the 5 situations considered.

TABLE I  
SIMULATED PATHOLOGICAL CONDITIONS

Condition	Lesion Position	Lesion Dimension	Source Position	Source Orientation
A	Superficial	Large	Below	Radial
B	Deep	Large	Below	Radial
C	Deep	Small	Internal	Tangential
D	Superficial	Large	Above	Radial
E	Deep	Large	Internal	Radial

By this way we tested the sensitivity of the dipole inverse solution to various levels of error committed in LCA in presence of various levels of noise.

We computed the mean absolute localization error and the maximum absolute localization error.

In the source reconstruction procedure a residual error estimate function  $\rho$  is minimized;  $\rho$  is defined as [7]:

$$\rho = \sqrt{\sum_{i=1}^{64} (V_{mi} - V_{ci})^2} / \sqrt{\sum_{i=1}^{64} (V_{mi})^2}$$

where  $V_{mi}$  is the measured (simulated) EEG potential and  $V_{ci}$  is the one produced by the reconstructed source at the  $i$ th electrode position. In a previous paper we found that in noiseless conditions the relation between conductivity ( $\sigma$ ) misassignment and the corresponding minimal  $\rho$  values could be approximated by a second order polynomial function. A closer inspection of the  $\rho$  distribution revealed two different linear trends for  $\sigma$ s above or below the real  $\sigma$ . We found that fitting separately the two distributions the real  $\sigma$  (actually unknown) can be estimated as the abscissa of the intersection of these two lines.

We apply the line intersection method with noisy EEG potentials selecting two sets of minimal  $\rho$  data with the following criterion: the 5 samples of the lesion conductivity space from -50% to -10% were used for fitting the first line; the samples from +10% to +100% (10 values) provided data for fitting the second line; we avoid to include in both data sets the correct conductivity value.

### III. RESULTS

We start showing the effect of noise (only) on source reconstruction accuracy. The localization errors due to the different levels of noise are shown in table 1. Although just one sample of noise has been considered and thus errors might vary, the huge difference between cases clearly indicates that sensitivity of noise depends upon SNR ratio (see case B) and, even more important, LE depends on source type, source-lesion and source electrodes relative positions. Sources reconstructed in case D, in which the sources were interposed between lesion and electrodes, exhibited a huge and constant LE, the intensity errors (IE) reached the 400% of actual values. For the other examples shown here IE was bound to less than 60%. Case C is an example of tangential source for which the effect of noise results minimal. The values shown in Table II are minimal absolute errors achievable applying the LIT to the four data sets, thus they constitute the reference for the error reduction method efficacy. Considering also lesion conductivity assignment errors source reconstruction became even less accurate.

TABLE II  
ABSOLUTE LE (mm) WITH CORRECT LCA

Case	SNR=5	SNR=10	SNR=15	SNR=∞
A	1.3	1.4	1.5	0.0
B	22.1	2.6	3.3	0.0
C	0.0	0.1	0.0	0.0
D	34.3	34.2	34.2	0.0
E	1.2	0.7	2.9	0.0

Table III summarized the obtained mean and maximum localization errors. In order to isolate the LCA contribution to LE on noisy data, for each SNR value, we evaluated also the difference between mean and baseline and the difference between maximum and baseline LE errors; data are shown in Table IV. In this contest the baselines are those LE values found with or without noise and with the correct LCA (see Table II). Comparing data in Table II and IV we observed that LCA could determine errors as large as noise or of one order of magnitude smaller. Fig. 2, shows an example (case A) of LE values for different levels of SNR and LCA errors. As can be seen in Fig. 2, in some cases, the sensitivity of LE to LCA diminishes as noise increases (curves became flatter).

Source estimation algorithm minimized  $\rho$ . This parameter gives an indication of similarity between the scalp potential generated by the actual and reconstructed sources. Both LCA errors and noise determine potential dissimilarity thus  $\rho$  increases. As can be seen in Fig. 3 the main effect of noise was a translation of  $\rho$  curves ( $\rho$  vs. LCA error) towards higher values. LCA error determines rather characteristic distribution of LE values, the curvature of the LE profile is reduced by noise (see Fig. 3 and 4). By applying the LIT method for error reduction we estimated lesion conductivity. From this estimate we could quantify the residual localization error (RLE) after LIT error reduction. These data are shown in Table V. In the same table, to quantify LIT efficacy, is shown also the difference between the RLE and the reference (baseline: LE values in Table II): the smaller these differences the better the performance.

TABLE III  
MEAN AND MAXIMUM ABSOLUTE LE (mm) WITH WRONG LCA

Case	error	SNR=5	SNR=10	SNR=15	SNR=∞
A	Mean	2.9	2.3	6.4	8.1
	Max	5.4	5.5	9.4	17.3
B	Mean	21.4	7.0	5.2	7.5
	Max	25.0	9.9	12.3	13.5
C	Mean	0.6	0.7	1.0	0.9
	Max	1.6	1.6	2.3	2.0
D	Mean	34.9	36.0	34.9	1.7
	Max	37.9	43.8	38.1	4.2
E	Mean	1.8	1.5	3.3	1.3
	Max	2.9	2.5	5.3	3.1

TABLE IV  
LE DUE TO LCA ERROR: MEAN AND MAXIMUM LCA EFFECT.

Case	Error	SNR=5	SNR=10	SNR=15	SNR=∞
A	Mean-baseline	1.6	0.9	4.9	8.1
	Max-baseline	4.1	4.1	7.9	17.3
B	Mean-baseline	0.7	4.4	1.9	7.5
	Max-baseline	2.9	7.2	9.0	13.5
C	Mean-baseline	0.6	0.7	1.0	0.9
	Max-baseline	1.6	1.6	2.3	2.0
D	Mean-baseline	0.7	1.9	0.6	1.7
	Max-baseline	3.7	9.6	3.9	4.2
E	Mean-baseline	0.6	0.8	0.4	1.3
	Max-baseline	1.7	1.8	2.4	3.1

The benefit (the LE reduction), is better described by the difference between residual error and mean or maximum localization errors (See Table VI). In this way we can quantify RLE relative to an expected error, either in mean or in maximum terms.

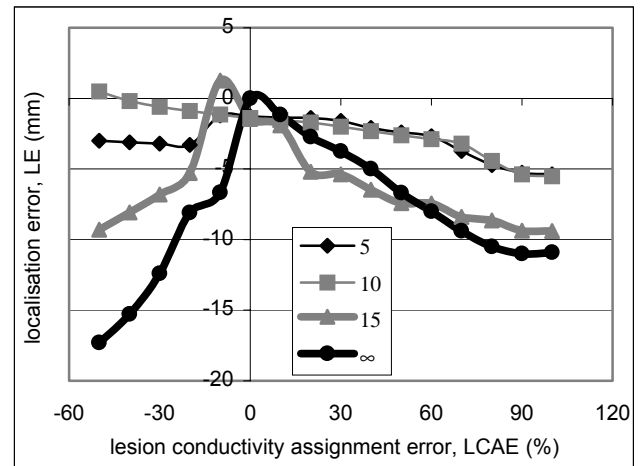


Fig 2. Localization errors (LE) for different SNRs (see legend) and for different lesion conductivity misassignments (case A)

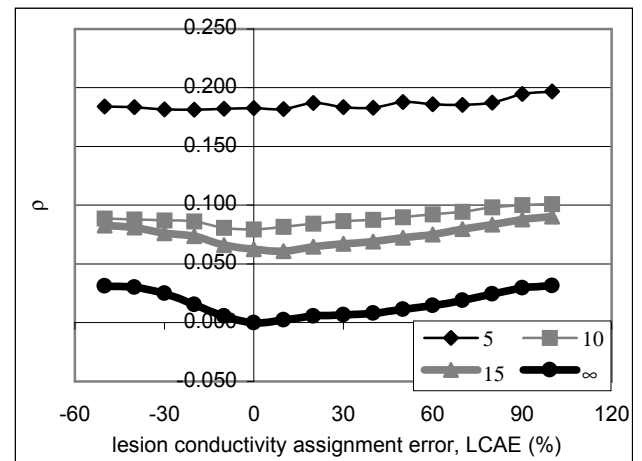


Fig 3.  $\rho$  values for different SNRs (see legend) and for different lesion conductivity misassignments (case C)

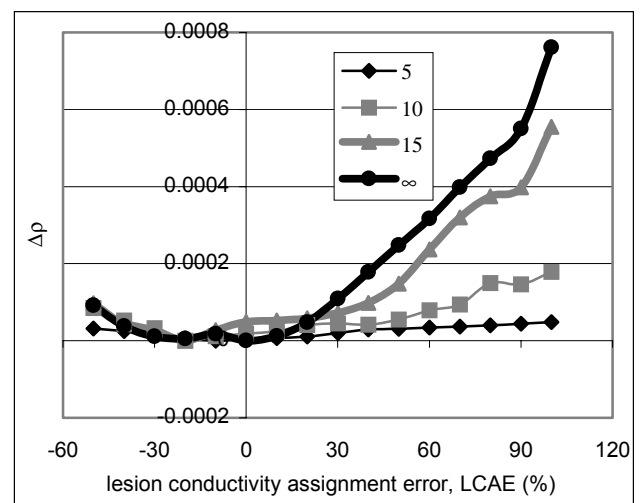


Fig 4. Modulation of  $\rho$  for different SNRs (see legend) and for different lesion conductivity misassignments (case B).  $\Delta\rho$  is the difference between  $\rho$  and its minimum.

TABLE V  
EFFICACY OF LIT ON CONDUCTIVITY ESTIMATE AND RLE DUE TO RESIDUAL CONDUCTIVITY ERROR.

Case		SNR=5	SNR=10	SNR=15	SNR= $\infty$
A	residual LCA error %	11	3	6	-2
	RLE-baseline (mm)	0.1	0.0	0.4	0.0
B	residual LCA error %	-12	-4	8	10
	RLE-baseline (mm)	0.6	0.0	0.4	2.2
C	residual LCA error %	3	4	9	5
	RLE-baseline (mm)	0.0	0.0	0.2	0.0
D	residual LCA error %	7	7	9	14
	RLE-baseline (mm)	0.4	0.2	0.9	0.4
E	residual LCA error %	-33	-8	-10	-13
	RLE-baseline (mm)	-0.8	-0.3	-0.6	0.3

Negative values in table VI indicate a residual error after conductivity estimate smaller than the mean or the maximum error expected for that condition. Comparing data shown in Tables IV and VI it is possible to observe that LE reduction can be almost complete, although in 3 conditions positive numbers appear. This means that the RLE is larger than the mean error due to LCA errors. This was true for mean errors only and for mean errors less of 1.7 mm.

#### IV. DISCUSSION

We selected the five conditions presented here on the base of the previous study [3] in which we proposed and quantified the efficacy of the reduction method (LIT) of localization errors due to LCA.

In absence of noise, case A was characterized by the largest LE error and, at the same time, the error reduction technique was very effective. Case B had also a large error but the residual error was larger than in case A, i.e. the LIT was less effective. Case C was the one for which the application of LIT did not determine LE reduction, but absolute LE values were anyway within few millimeters. D provided an example of large reduction of LE although the initial maximum localization error was only about 4 mm. Finally, E was the case of internal source for which LCA estimation was not so good but the LE reduction optimal.

The implementation of LIT in this study was somehow suboptimal, since the two sets had different number of elements and, more important, one of them could contain wrong samples. This implementation does not provide the best lesion conductivity estimate [3] but, for seek of a test, was a conservative approach to LIT robustness and performances. The 33% of conductivity estimate error found in case D can be explained considering this suboptimal implementation.

TABLE VI  
MEAN AND MAXIMUM ERROR REDUCTION AFTER LIT.

Case		SNR=5	SNR=10	SNR=15	SNR= $\infty$
A	RLE-mean (mm)	-1.5	-0.9	-4.4	-8.1
	RLE-max (mm)	-4.0	-4.1	-7.5	-17.3
B	RLE-mean (mm)	-0.1	-4.4	-1.5	-5.3
	RLE-max (mm)	-2.3	-7.3	-8.6	-11.3
C	RLE-mean (mm)	-0.6	-0.7	-0.8	-0.9
	RLE-max (mm)	-1.6	-1.6	-2.2	-2.0
D	RLE-mean (mm)	-0.3	-1.7	0.3	-1.3
	RLE-max (mm)	-3.2	-9.4	-3.0	-3.8
E	RLE-mean (mm)	0.2	-0.4	0.2	-0.9
	RLE-max (mm)	-0.9	-1.5	-1.8	-2.8

The LIT allowed an estimation of lesion conductivity with an accuracy sufficient to keep the additional (residual) LE error due to LCA misassignment within 1 mm with noisy data and 2.2 mm without noise. The accuracy of source localization is then dependent on SNR, i.e. on the noise reduction achievable during recording and data processing. Interestingly, it seems that the noise can reduce the sensitivity of source localization procedure to LCA error. LIT allowed to always find smaller LE than maximum absolute LE due to LCA errors.

Cuffin [8] reported that noise and modeling errors determine source LE of similar entity; we analyzed a peculiar type of parametric model error, which, indeed, could induce LE comparable with noise. However, we demonstrated that LE due to the parametric error is avoidable even with EEG noise. It is known that a linear relation exists between noise level and LE, however this relation shows up only in mean terms. We considered only one noise distribution, therefore it is not surprising that noise level and LE are not well correlated. Moreover, has been proved that noise effect depends on electrodes number and placement, thus a direct comparison of our results with previous works is difficult.

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