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Cortical Potential Imaging of Brain Electrical Activity by Means of Parametric Projection Filter

J. Hori[1*], J. Lian[1], B. He[1, 2]
[1]Department of Bioengineering and [2]Department of ECE, University of Illinois at Chicago, Chicago, USA
[*]Present address: Department of Biocybernetics, Niigata University, Niigata, Japan

Summary

Objectives: The objective of this study was to explore suitable spatial filters for inverse estimation of cortical potentials from the scalp electroencephalogram. The effect of incorporating noise covariance into inverse procedures was examined by computer simulations and tested in human experiment.
Methods: The parametric projection filter, which allows inverse estimation with the presence of information on the noise, was applied to an inhomogeneous three-concentric-sphere model under various noise conditions in order to estimate the cortical potentials from the scalp potentials. The method for determining the optimum regularization parameter, which can be applied for parametric inverse techniques, is also discussed.
Results: Human visual evoked potential experiment was carried out to examine the performance of the proposed restoration method. The parametric projection filter gave more localized inverse solution of cortical potential distribution than the truncated SVD and Tikhonov regularization.
Conclusion: The present simulation results suggest that incorporation of information on the noise covariance allows better estimation of cortical potentials, than inverse solutions without knowledge about the noise covariance, when the correlation between the signal and noise is low.

Keywords
High resolution EEG, cortical potential imaging, inverse problem, parametric projection filter, noise covariance

Methods Inf Med 2004; 43: 66–9

1. Introduction

Brain electrical activity is spatially distributed over three dimensions of the brain and evolves in time. Electroencephalography (EEG) has historically been a useful modality to provide high temporal resolution regarding the underlying brain electrical activity. However, the spatial resolution of EEG is limited due to the smearing effect of the head volume conductor. In the past decades, much effort has been made in the development of high-resolution EEG techniques, which attempt to image and map spatially distributed brain electrical activity with substantially improved spatial resolution without *ad hoc* assumption on the number of source dipoles (for review, see [1]).

Of particular interest is the recent development of cortical imaging approaches, in which an explicit biophysical model of the passive conducting properties of the head is used to deconvolve a measured scalp potential distribution into a distribution of electrical potential on the cortical surface [1-11]. Because the cortical-potential distribution can be experimentally measured [4, 12, 22] and compared to the inverse imaging results, the cortical-potential imaging approach is also of physiologic importance.

In parallel to the development of physical models for cortical potential imaging, the inverse regularization algorithm plays an important role in cortical imaging. Regularization strategies, such as general inverse with truncated singular value decomposition (TSVD), constrained least square method, and Tikhonov regularization method (TKNV), have been used to solve the ill-conditioned cortical imaging inverse problem (for review, see [1]). Several investigators have further explored the use of advanced regularization methods to improve the cortical imaging inverse results. Especially, Weiner reconstruction frameworks based on both signal and noise covariances have been investigated [13-16].

In the present study, we hypothesize that a regularization approach incorporating information about noise covariance alone would improve the restorability of cortical potentials from scalp potentials, meanwhile eliminating the difficulty of estimating signal covariance. Since the noise covariance could be estimated from pre-stimulus evoked potentials, the proposed approach is practically feasible, while taking into consideration the statistical properties of measurement noise. We investigated the equivalent dipole layer imaging by means of parametric projection filter (PPF), in which the noise covariance was taken into consideration [17]. In the present study, we examine the applicability of PPF to cortical potential imaging through computer simulations and experimental studies. We have also improved the algorithm to determine the regularization parameter.

2. Method

2.1 Principles of Cortical Potential Imaging

In the present cortical potential imaging study, the head volume conductor is approximated by the inhomogeneous three-concentric sphere model and a closed dipole layer of 1280 dipoles is used [8]. This head model takes the variation in conductivity of different tissues, such as the scalp, the skull and the brain, into consideration. The detail

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of the cortical potential imaging technique being used in the present study is shown in [8]. The observation system of brain electrical activity on the scalp shall be defined by the following equation:

$$g = A f + n \tag{1}$$

where f is the vector of the equivalent source distribution of a dipole layer, n is the vector of the additive noise and g is the vector of scalp-recorded potentials. A represents the transfer matrix from the equivalent source to the scalp potentials. The inverse process shall be defined by

$$f_0 = B g \tag{2}$$

where B is the restoration filter and f_0 is the estimated source distribution of the dipole layer. Once f_0 is estimated, the potential distribution on the cortical surface can be calculated through forward solution using the transfer matrix from the equivalent dipole layer to the cortical potentials [8].

2.2 Inverse Techniques

In the presence of noise, the truncated singular value decomposition (TSVD) can be used to calculate the pseudoinverse filter. Moreover, Tikhonov regularization method (TKNV) can be used, which leads to

$$B = A^* (A A^* + \gamma I)^{-1} \tag{3}$$

where γ is a small positive number known as the regularization parameter, I the identity matrix and A^* the transpose matrix of A. The parametric projection filter (PPF), which allows estimating solutions in presence of information on noise covariance structure, has been introduced to solve the inverse problem [18]. The PPF is given by

$$B = A^* (A A^* + \gamma Q)^{-1} \tag{4}$$

where Q is the noise covariance derived from the expectation over the noise ensemble $E[nn^*]$. The determination of the value of parameter γ is left to the subjective judgment of the user. We have applied the parametric projection filter to the inverse problem described by Eq. (2). In a clinical and experimental setting, the noise covariance may be estimated from data that is known to be source free, such as pre-stimulus data in evoked potentials [16].

2.3 Parameter Estimation

The restoration filters have a free parameter that determines the restorative ability. We have developed a new criterion for determining the optimum parameter without knowing the original source distribution. One possibility is to use the following procedure.

1) Compute the restoration f_0 using an initial value for γ, which should be relatively large to reduce the effect of additive noise on the coefficients.
2) Calculate the following function:

$$J(\gamma) = \|f_0 - BAf_0\|^2 + tr[BQB^*] + \\ + 2(Bg - BAf_0, f_0 - BAf_0). \tag{5}$$

3) Obtain new parameter γ_1 by minimizing Eq. (5).
4) Repeat 1) - 3) using new γ_1 until $\|\gamma - \gamma_1\| / \|\gamma\| < e$ where e is a preset small number.

In the previous parameter determination proposed in [17], the last term on the right hand side of Eq. (5), which corresponds to the inner product between restored noise and restorative error, was approximated by zero. In the present study, this term was kept in Eq. (5), and based on our experience, it will improve the inverse results because the correlation between signal and noise is negligible. The computer simulation results suggest that this procedure also provides the unique solution of γ despite of varying the initial value.

2.4 Human Experimentation

Human visual evoked potential (VEP) experiment was carried out to examine the performance of the proposed restoration method. One healthy subject was studied in accordance with a protocol approved by the Institutional Review Board of the University of Illinois at Chicago. 96-channel VEP signals referenced to right earlobe were amplified with a gain of 500 and band-pass filtered from 1 Hz to 200 Hz, and were acquired at a sampling rate of 1 kHz. Half visual field pattern reversal check boards with reversal interval of 0.5 sec served as visual stimuli and 400 reversals were recorded to obtain averaged VEP signals.

3. Results

3.1 Simulation Results

Figure 1 shows an example of the normalized cortical and scalp potentials calculated directly from two radial dipoles with eccentricity of 0.75. The scalp potentials measured with 128 electrodes were contaminated with 10% edge-concentrated noise. Note that the two poles in the cortical potential distribution (a) are indistinguishable in the scalp potential distribution (b).

Figure 2 shows the relative error versus the eccentricity of dipoles in three inverse techniques. Two dipoles, located at the center position with varying eccentricity were used as the sources. In the case of center-concentrated distribution of dipole as shown in Figure 1a, the present method was effective for edge-concentrated non-uniform noise. The results of the present method were similar to that of the TSVD and the TKNV in the cases of the Gaussian white

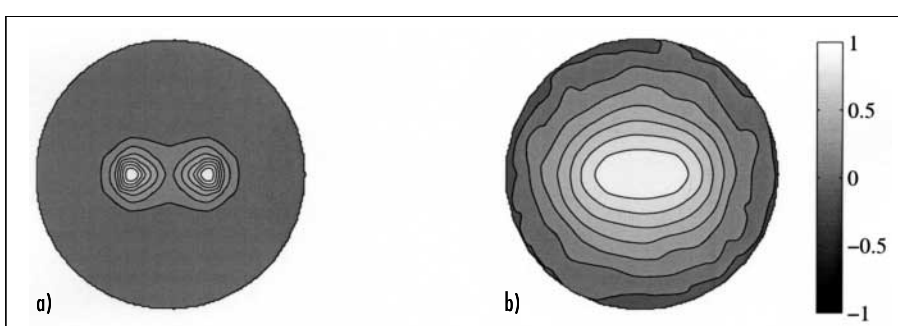

Fig. 1 One example of the normalized (a) cortical and (b) scalp potentials. Two radial dipoles were located with the eccentricity of 0.75.

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noise and one-side or center-concentrated non-uniform noise.

Figure 3 shows an example of the inverse solution of the estimated cortical potential distribution. The eccentricity of two radial dipoles was 0.75. 10% edge-concentrated non-uniform noise was added to the scalp potential. Figure 3a shows the analytic cortical potential distribution. It is clear that the PPF (Fig. 3d) has better performance in reconstructing the two radial dipole sources as compared to the TSVD (Fig. 3b) and TKNV (Fig. 3c) methods.

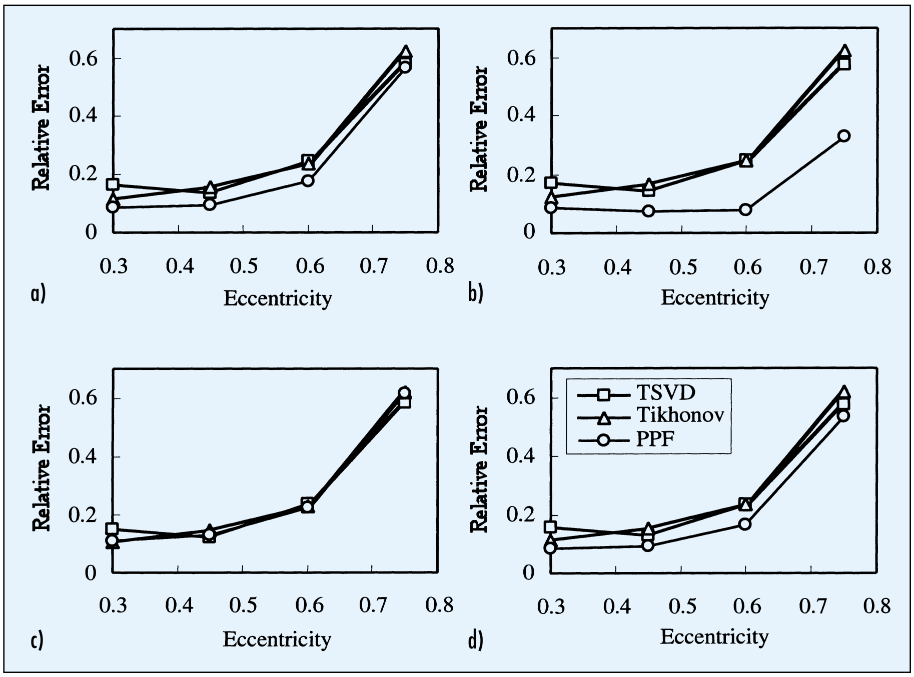

Fig. 2 Eccentricity vs. relative errors. The scalp potentials were contaminated with (a) GWN and (b) edge-, (c) center-, and (d) on side-concentrated non-uniform noise.

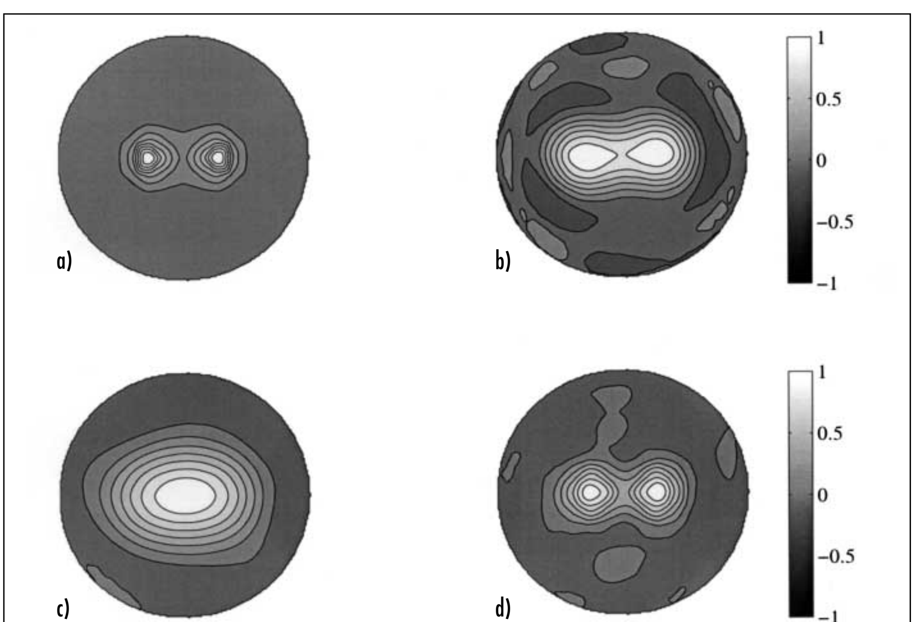

Fig. 3 One example of the estimated inverse solutions of cortical potential imaging. A 10% edge-concentrated non-uniform noise was added to the scalp potential (a) Actual cortical potential map. Cortical potential maps estimated by the (b) TSVD, (c) TKNV, and (d) PPF.

3.2 Application to the VEP Experiment

The pattern reversal VEP data at the P100 were analyzed by the restoration filters of the TSVD, TKNV, and PPF. Figure 4 shows an example of the normalized scalp potential map and the estimated cortical potential maps in a healthy subject. As shown in Figure 4a in response to the left visual field stimuli, a dominant positive potential component was elicited with a widespread distribution on the bilateral scalp. However, the estimated cortical potential map reveals a dominant in the right visual cortex. Note that the PPF (Fig. 4b) gives more localized inverse solution than the TSVD (Fig. 4c) and TKNV (Fig. 4d).

4. Discussion

Research progress in the past decade has established the high-resolution EEG methodologies for imaging brain electrical activity. The cortical imaging approaches are virtually applicable to any kind of brain source distribution (both localized and distributed) [1]. This is due to the generalized nature of the equivalent surface source models behind the cortical imaging techniques. These techniques should be useful particularly for localizing and imaging cortical sources.

Noise plays an important role in cortical potential imaging, as in any other ill-posed inverse problem. In the present study, we have investigated the performance of cortical potential imaging by considering noise covariance through the use of parametric projection filter. The present study demonstrates that enhanced performance can be obtained in cortical potential imaging by considering the noise covariance.

The present results suggest that the proposed method is effective in improving performance of cortical imaging, under the condition of low correlation between signal and noise. The present method would have

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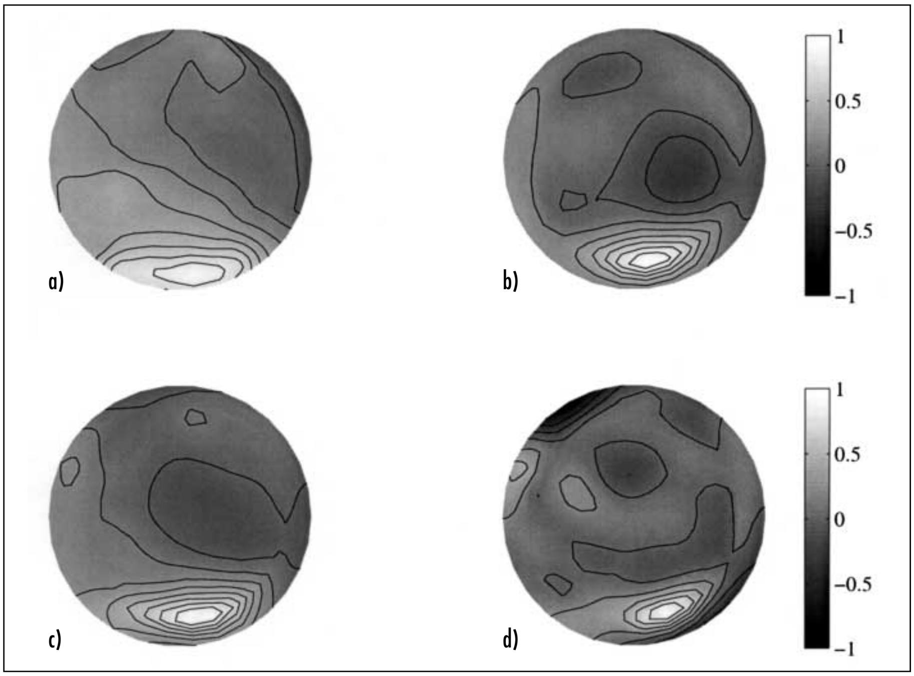

Fig. 4 Application of the restoration filters to cortical potential imaging in human subject. (a) Scalp potential map recorded at P100 in response to the left visual stimuli. Cortical potential maps estimated by the (b) TSVD, (c) TKNV, and (d) PPF.

similar restorative ability to the regularization procedures without considering the information of noise covariance, under the condition of high correlation between signal and noise. Therefore, using the present PPF approach will improve the performance of cortical potential imaging, considering the general cases that there is no high correlation between signal and noise.

Parameter estimation methods in conventional regularization procedures have been used in cortical potential imaging, such as the L-curve approach [19], zero-crossing approach [20], and minimum product approach [21]. The present parameter estimation method is directly derived from the aim of this study that minimizing the error between the original and estimated signal. The present algorithm for determining the regularization parameter may be applied to other parametric inverse estimation procedures, such as the TSVD, TKNV, etc.

Acknowledgments
This work was supported in part by a Grant-In-Aid for Scientific Research from Japanese Society for the Promotion of Science, NSF BES-9875344, NSF BES-0218736, and NIH EB00178.

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Correspondence to:
Dr. Junichi Hori
Department of Biocybernetics
Niigata University
8050 Ikarashi-2, Niigata 950-2181, Japan
E-mail: hori@bc.niigata-u.ac.jp

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