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EEG Current Source Localization Using Deep Prior

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Abstract

The estimation of current sources in the brain from magnetoencephalogram (MEG) or electroencephalogram (EEG) is generally an underdetermined problem. Many conventional methods uniquely estimate the current source by explicitly assigning a prior distribution of current sources. In our previous work, we proposed a method for solving the MEG inverse problem using an implicit prior of an untrained convolutional neural network (CNN), which is called Deep Prior, and showed that the CNNs can represent the prior distribution of current sources. However, MEG measurement requires large-scale equipment and it is desirable to estimate the current source from EEGs, which can be measured more easily. In this paper, we propose a method to estimate current sources from EEGs using Deep Prior, and show that it is more accurate than the conventional methods. We also show that linearizing the network structure improves the localization accuracy.

1. Introduction

Magnetoencephalogram (MEG) and electroencephalogram(EEG) are non-invasive measurements of human brain activities that provide excellent temporal resolution. The estimation of current sources in the brain using MEG and EEG has helped to elucidate brain function and assist in the diagnosis of brain diseases. However, estimating the current distribution in the brain is inherently difficult because it is an underdetermined problem with a small number of MEG/EEG sensors relative to the number of current source parameters.

Conventional methods for current source estimation, such as minimum norm estimation (MNE) [1] and standardized low-resolution brain electromagnetic tomography (sLORETA) [2], solve this problem by explicitly giving the prior distribution of the current source. However, it is difficult to obtain the prior distribution of the actual current sources, and estimation based on an incorrect prior distribution may result in a large error.

In recent years, deep convolutional neural networks (CNNs) have been shown to play a role in the prior distribution of natural images. This implicit image prior is called Deep Image Prior and has been shown to be effective for inverse problems in the image field [3]. In our previous work [4], we proposed a method for solving the MEG inverse problem using an implicit prior of an untrained CNN (Deep Prior), and showed that the CNNs can represent the prior distribution of current sources. However, MEG measurement requires large-scale equipment and it is desirable to estimate the current source from EEGs, which can be measured more easily.

In this paper, we propose a method to estimate current sources from EEGs using Deep Prior, and show that it is more accurate than the conventional methods. We also show that linearizing the network structure improves the localization accuracy. In recent years, an implicit bias of gradient descent on deep linear neural networks has been shown [5]. Therefore, linearization can be effective in the estimation of the current sources.

2. Formulation of Current Source Estimation

2.1 MEG/EEG Forward Problem

Finding the magnetic field or electric potential observed by sensors when current sources in the brain are given is called a " forward problem ". In this work, by discretizing a given region in the brain and fixing the position of the current source on the mesh point, the magnetic field or electric potential $\boldsymbol{v} \in \mathbb{R}^M$ observed by the sensor can be expressed in the form of the product of the lead field matrix $\boldsymbol{L}$ and the current vector $\boldsymbol{q} \in \mathbb{R}^{3N}$:

$$\boldsymbol{v} = \boldsymbol{L}\boldsymbol{q} \tag{1}$$

where M is the number of sensors and N is the number of mesh points. The lead field matrix $\boldsymbol{L}$ is given by numerical calculation, such as the boundary element method, using magnetic resonance imaging (MRI) data, which is based on the position of the sensor, the position of the mesh point, and the conductivity in the brain.

2.2 MEG/EEG Inverse Problem

The inverse of a forward problem is finding the current source in the brain from the observed magnetic field or electric potential containing noise. This is commonly referred to as an "inverse problem". When the brain is discretized, the number of current sources becomes very large compared to the number of sensors. This makes it difficult to uniquely obtain the current source from the observed magnetic field or electric potential. This is also called an "ill-posed problem".

Conventional methods, such as MNE and sLORETA, assume the multivariate normal distribution for the prior distribution of noise and current sources contained in the observed values, and minimize the sum of the error and the regularization term between the forward problem and the observed value $\boldsymbol{v_{obs}}$. It gives us an estimation $\hat{\boldsymbol{q}}$:

$$\hat{\boldsymbol{q}} = \underset{q}{\operatorname{argmin}} \, \mathrm{E_C}(\boldsymbol{Lq}; \boldsymbol{v_{obs}}) + \lambda \boldsymbol{q}^\top \boldsymbol{S}^{-1} \boldsymbol{q} \tag{2}$$

$$= \boldsymbol{SL}^\top (\boldsymbol{LSL}^\top + \lambda \boldsymbol{C})^{-1} \boldsymbol{v_{obs}} \tag{3}$$

where $\boldsymbol{S}$ is the covariance matrix of the parameters of the current source, and $\boldsymbol{C}$ is the covariance matrix of the noise in the sensor. However, it is difficult to obtain the probability distribution of the actual current source, and an estimation based on a prior distribution that differs from the actual one may result in a large error.

3. EEG current source estimation using Deep Prior

Figure 1 shows the overview of the EEG current source estimation using Deep Prior. When carrying out current source estimation using Deep Prior, the current $\boldsymbol{q}$ is generated by neural network $\boldsymbol{f_\phi}(\boldsymbol{z})$ with the latent variable $\boldsymbol{z}$ as input, and the network parameters ϕ are estimated so that the observation error is minimized. In our method, $\boldsymbol{q}$ in (2) is replaced by the output $\boldsymbol{f_\phi}(\boldsymbol{z})$ of the neural networks. The solution of the current source estimation using Deep Prior is as follows:

$$\hat{\boldsymbol{\phi}} = \underset{\phi}{\operatorname{argmin}} \, |\boldsymbol{v_{obs}} - \boldsymbol{L f_\phi}(\boldsymbol{z})|_2^2 \tag{4}$$

$$\hat{\boldsymbol{q}} = \boldsymbol{f_{\hat{\phi}}}(\boldsymbol{z}) \tag{5}$$

where each element of the latent variable $\boldsymbol{z}$ is sampled from the multivariate standard normal distribution. This method requires only a noisy EEG observation $\boldsymbol{v_{obs}}$ at a single time point. The network parameters ϕ are randomly initialized. The updating of ϕ was stopped before $\boldsymbol{L f_\phi}(\boldsymbol{z})$ is fitted to the observed noise.

In order to suppress the spread of the predicted current source, the hard shrinkage function $H(x)$ was used in the final layer of the network $\boldsymbol{f_\phi}(\boldsymbol{z})$.

$$H(x) = \begin{cases} x & (|x| \geq T) \\ 0 & (|x| < T) \end{cases} \tag{6}$$

where T is threshold of 25 % of the maximum value.

The size of the final layer of the network corresponds to the arrangement of mesh points. The number of channels in the final layer was set to 3 corresponding to the x, y, and z components of the current source vectors. From the output of the final layer, the components of the current vector only in the brain region were extracted and used as the final output of the network.

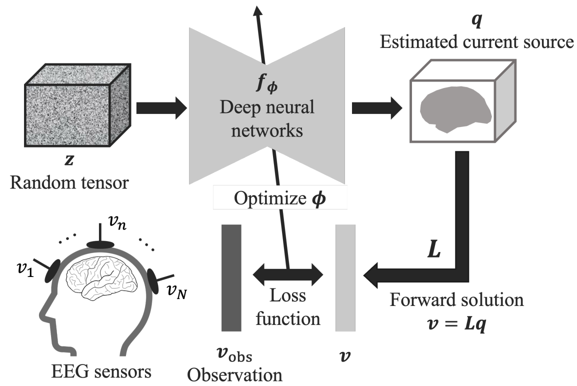

Figure 1: EEG current source estimation in the brain using Deep Prior

4. Evaluation experiment

Current source estimation was performed on artificially generated EEG data. A head model of a subject and the settings of an EEG system in the MNE-Python sample dataset [6] were used as the simulation environment. The EEG measurement system has a total of 60 sensors. A current dipole source was placed in the center of the primary auditory cortex of the right hemisphere (rA1) or the primary somatosensory cortex of the right hemisphere (rS1) in the brain. Multivariate Gaussian noises were added to the EEG signals generated from the current dipole. The signal-to-noise ratio (SNR) was set at 20, 5, 2, and 0 dB.

Since the current distribution estimated by the Deep Prior-based method is not unique due to the nonlinear optimization of ϕ, 20 current distributions estimated with different initial parameters of ϕ from each other were averaged. The number of the parameter updates for each estimation was less than or equal to 100. To investigate the effects of the network architecture on current estimation, a linear U-Net architecture without activation functions and a nonlinear U-Net architecture with activation functions were used.

The performance of the current estimation using Deep Prior was evaluated on the localization error of the current dipole, and the results were compared to conventional methods, MNE and sLORETA. MNE and sLORETA were implemented by MNE-Python. The localization error was defined as the Euclidean distance between the actual test source and the estimated location of the maximum amplitude in the estimated current source distribution. The average values of 10 estimations for each method were compared.

5. Results and Discussion

The electric potential distributions on the sensors for the dipole source in the rA1 after 10, 100, 300, and 500 parameter updates are shown in Figure 2, where 'True' is the distribution of sensor observation without noise, and 'Observation' is the distribution of sensor observation given to the estimation. When the number of parameter updates was 500, the loss function decreases continuously. The distribution of the estimated sensor observation at the 100th parameter update is close to the distribution of the observation without noise, even though the observed values with 0 dB of noise superimposed on them were trained as a training data. As the number of iterations increases, the distribution of the estimated sensor output approaches the distribution of the noisy observation. This indicates a denoising effect of Deep Prior: low-frequency components included in the signal are learned first, and high-frequency components included in the noise are learned later. Although the loss function continues to decrease, the true signal can be estimated by stopping the learning process on the way to local minima.

Table 1 shows the localization error of the current source position estimated from the EEG when the current source is placed in the rA1. The localization error of the proposed method is less than that of MNE and sLORETA, even when the SNR is varied. The performance of the current source estimation using Deep Prior with the linear U-Net architecture was more accurate than the performance of the current source estimation using Deep Prior with the nonlinear U-Net architecture.

The estimated current distributions are shown in Figure 3, where the actual current source was placed in the rA1. As shown in Figure 3, the current distributions estimated by MNE and sLORETA were spread out and distributed throughout the brain. On the other hand, the current distribution estimated by the proposed method was a narrow distribution centered on the actual current source location.

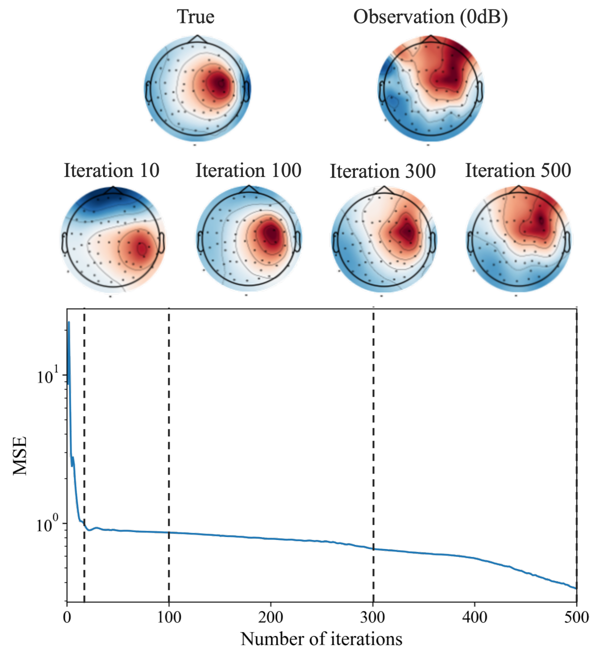

Figure 2: Observed EEG sensor at rA1 for each number of parameter updates

Table 1: Localization error of the current dipole in the rA1

Method	Localization Error [mm]			
	20 dB	5 dB	2 dB	0dB
MNE	45.3	44.4	46.4	52.4
sLORETA	17.9	27.1	38.5	38.2
Ours (Linear U-Net)	**10.0**	**13.3**	**16.1**	**21.6**
Ours (Nonlinear U-Net)	12.0	16.8	22.5	27.9

Table 2: Localization error of the current dipole in the rS1

Method	Localization Error [mm]			
	20 dB	5 dB	2 dB	0dB
MNE	21.5	21.5	21.3	34.9
sLORETA	13.5	13.5	14.0	13.5
Ours (Linear U-Net)	**9.1**	**9.1**	**10.3**	**11.5**
Ours (Nonlinear U-Net)	11.8	10.3	10.5	12.4

Table 2 shows the localization error of the current source position estimated from the EEG when the current source is placed in the rS1. The position error of the proposed method, as well as rA1, is less than that of MNE and sLORETA, even when the SNR is varied.

The performance of the current source estimation when using Deep Prior with the linear U-Net architecture was also more accurate than the performance of the current source estimation using Deep Prior with the nonlinear U-Net architecture. In general, nonlinear activation functions are used in CNNs for image generation tasks. However, the current distribution assumed in this study does not necessarily have a complex structure like a natural image, and the linear structure may be adequate for modeling current density in the brain. In addition, optimizing linear multilayer neural networks through gradient descent leads to a low-rank solution [5]. The property is known as implicit regularization or implicit bias. The bias may have facilitated learning of low-rank solutions that include the signal, and improved the accuracy of current source estimation.

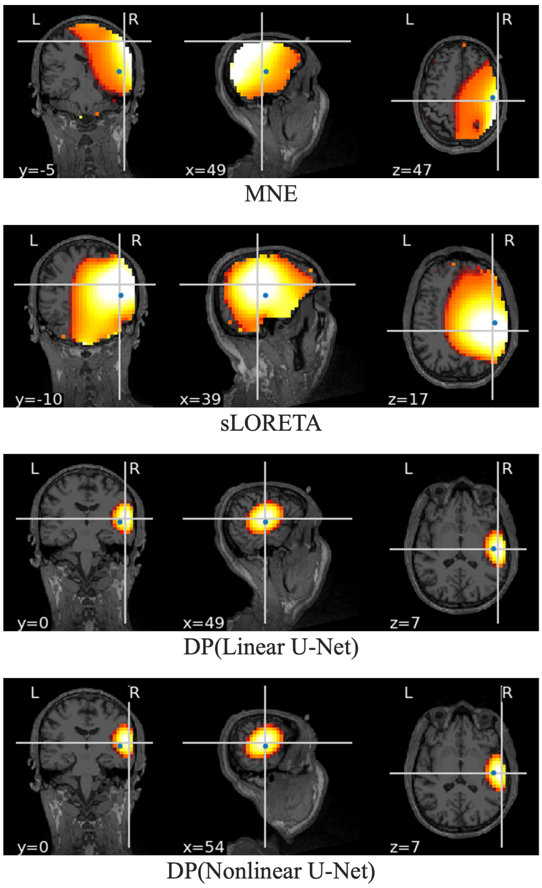

Figure 3: Estimated current sources from EEG generated by the current dipole in the rA1

6. Conclusions

In this work, we proposed an EEG source estimation method using Deep Prior. EEG data are easier to measure than MEG data. In our experiments, the EEG data synthesized by assuming a signal current source in the rA1 and the rS1 were used, and the results showed that the localization error was reduced and the current source was able to be better estimated around the true position compared to the conventional methods, MNE and sLORETA. Furthermore, we showed that using a linear U-Net structure without activation functions can provide better position estimation with fewer errors than the other methods due to the implicit regularization bias. Moreover, the denoising effect of Deep Prior was shown to restore a noise-free signal from a noisy observation.

Although the proposed method can estimate current sources from only a noisy observation, it requires a subject's head structure data, such as an MRI, to obtain a lead field matrix. The MRI measurements are time-consuming and burdensome for the subject. To readily estimate current sources in the brain, an estimation method without MRI data is desired.

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