Current Source Localization Using Deep Prior with Depth Weighting

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Abstract—This paper proposes a novel neuronal current source localization method based on Deep Prior that represents a more complicated prior distribution of current source in the brain using convolutional neural networks. Deep Prior has been suggested as an unsupervised learning approach that does not require a large amount of training data, and randomly-initialized neural networks are used as implicit priors for solving inverse problems. In previous work, a Deep-Prior-based current source localization method has been proposed but the performance was not almost the same as those of conventional approaches, such as standardized low-resolution brain electromagnetic tomography (sLORETA). In order to improve the Deep-Prior-based approach, in this paper, a depth weight of the current source is introduced for Deep Prior, where depth weighting amounts to assigning more penalty to the superficial currents. Its effectiveness is confirmed by experiments of current source estimation on simulated MEG data.

I. INTRODUCTION

Magnetoencephalography (MEG) and electroencephalography (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 been 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 neural networks (DNNs) trained with a large amount of data have been successful in many fields. The DNNs are capable of modeling complex associations among the data. There are a few studies on MEG/EEG source localization using DNN architectures, such as the multi-layer perceptron [3], convolutional neural networks (CNNs) [4], and long short-term memory [5]. In these studies, the networks were trained with artificially-generated MEG/EEG data by placing current sources in the brain due to the difficulty of collecting a large amount of actual MEG/EEG data and the impossibility of knowing true current sources in the brain. However, if the distribution of the artificial data does not sufficiently approximate that of the actual data, the DNNs trained with the artificial data may erroneously estimate current distributions. Moreover, it takes excessive computation time to train a DNN with a large number of parameters.

CNNs, even if untrained, 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 [6]. In our previous work [7], we proposed a method for solving the MEG inverse problem using an implicit prior of an untrained CNN (Deep Prior), and showed that the convolutional neural networks can represent the prior distribution of current sources. This method requires only a noisy MEG observation at a single time point. Parameter optimization of a generator network that includes convolutional layers is started with randomly initialized parameters and stopped before the generator reconstructs the noisy current density and MEG observation. However, the estimation error of the current source localization using Deep Prior was not almost the same as that of the conventional method, sLORETA, and there was still room for improvement with Deep Prior.

In this paper, we propose a solution that takes into account the depth weight of the current source to improve the current source localization accuracy using Deep Prior. It is known that the current density values estimated by MNE tend to be higher near the brain surface, and the MNE with depth weighting improves the localization accuracy [8]. Also, as the solution obtained using Deep Prior may have some bias, it is expected to be improved by taking the depth weight into consideration. In this study, we evaluated the localization error of the current source using artificially-generated MEG data assuming a single current source in the brain, and the performance of Deep Prior with depth-weighted regularization was compared to those of conventional methods.

II. FORMULATION OF CURRENT SOURCE ESTIMATION

A. MEG Forward Problem

Finding the magnetic field 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 \( b \in \mathbb{R}^M \) observed by the sensor can be
expressed in the form of the product of the lead field matrix $L$ and the current vector $q \in \mathbb{R}^{1 \times N}$:

$$b = Lq$$

where $M$ is the number of sensors and $N$ is the number of mesh points. The lead field matrix $L$ is given by numerical calculation, such as the boundary element method, which is based on the position of the sensor, the position of the mesh point, and the conductivity in the brain.

B. MEG Inverse Problem

The inverse of the forward problem is to find the current source in the brain from the observed magnetic field containing noise. This is commonly referred to as the “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. 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 $b_{\text{obs}}$. It gives us an estimation $\hat{q}$:

$$\hat{q} = \arg \min_q [E_C(Lq;b_{\text{obs}}) + \lambda q^T S^{-1} q]$$

where $s_k$ is the covariance matrix of the noise in each component $k$, and $p$ is a depth weighting parameter. $l_{3k-2}$, $l_{3k-1}$, and $l_{3k}$ correspond to the lead fields of the $x$, $y$, and $z$ components of the $k$-th current source, respectively.

III. DEPTH WEIGHTING

Since MNE minimizes the observation error under the squared weighted norm constraint of the brain currents, the current density values estimated by MNE tend to be higher near the brain surface. In order to compensate for it, a depth-dependent factor is introduced for the covariance matrix $S$ of the prior distribution of the currents [8].

$$s_k = \left(l_{3k-2}l_{3k-2}^T + l_{3k-1}l_{3k-1}^T + l_{3k}l_{3k}^T \right)^{-p}$$

Here, $l_i$ is the $i$-th column vector of the lead field matrix $L$ and $p$ is a depth weighting parameter. $l_{3k-2}$, $l_{3k-1}$, and $l_{3k}$ correspond to the lead fields of the $x$, $y$, and $z$ components of the $k$-th current source, respectively. Since each component of the lead field matrix is smaller for current sources located farther away from the sensor, i.e., deeper in the brain, the corresponding value of $s_k$ becomes larger. Therefore, given by $s_k$, the variance of the prior distribution of the currents at deeper locations increases, making it easier to estimate the currents at deeper locations. Also, depth weighting amounts to assigning more penalty to the superficial currents.

IV. DEEP PRIOR WITH DEPTH WEIGHTING

When carrying out current source estimation using Deep Prior, the current $q$ is generated by neural networks $f_\phi(z)$ with the latent variable $z$ as input, and the network parameters $\phi$ is estimated so that the observation error is minimized. In our method, $q$ in (2) is replaced by the output $f_\phi(z)$ of the neural networks and the covariance matrix $S$ of the current is modified using (5) in order to perform depth-weighted estimation. When taking depth weight into consideration using Deep Prior to solve an inverse problem, the solution of the current source estimation is as follows:

$$\hat{q} = \arg \min_\phi [E_C(Lf_\phi(z); b_{\text{obs}}) + \lambda f_\phi(z)^T S^{-1} f_\phi(z)]$$

where each element of the latent variable $z$ is sampled from the multivariate standard normal distribution. This method requires only a noisy MEG observation $b_{\text{obs}}$ at a single time.
point. Parameter optimization of the network is started with random initialized parameters and stopped before the network reconstructs the noisy current density and \( b_{\text{obs}} \).

Fig. 1 shows the overview of current source estimation using Deep Prior with depth weighting. 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.

V. EVALUATION EXPERIMENT

Current source estimation was performed on artificially-generated MEG data. A head model of a subject and settings of an MEG system in MNE-Python sample dataset [9] were used as the simulation environment. The MEG measurement system has a total of 306 sensors, consisting of 204 planar gradiometers and 102 magnetometers. A current dipole source with an intensity of 50 nAm was placed in the center of the primary auditory cortex of the right hemisphere (rA1) or primary visual cortex of the right hemisphere (rV1) in the brain. Multivariate Gaussian noises were added to the MEG signals generated from the current dipole. The noise level was equivalent to that after averaging over 80 MEG epochs. The signal-to-noise ratio (SNR) was 16.6 and 10.9 dB for the current dipole in the rA1 and rV1, respectively. The noise covariance matrix was computed from a noise recording in the dataset.

Since the current distribution estimated by the Deep-Prior-based method is not unique due to the nonlinear optimization of \( \phi \), 50 current distributions estimated with different initial parameters of \( \phi \) from each other were averaged. The number of the parameter updates for each estimation was less than or equal to 200. To investigate the effects of the network architecture on the current estimation, the U-Net (DP-UNet) and decoder (DP-Dec) architectures were used. The U-Net architecture used in [6] was adjusted to the current estimation. The decoder architecture was made by omitting the encoder architectures and skip connections from the U-Net architecture. The input of the decoder was a 128-dimensional random vector.

The performance of the current estimation using Deep Prior with depth weighting was evaluated on the localization error of the current dipole, and the results were compared to conventional methods, MNE and sLORETA. 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. MNE and sLORETA were implemented by MNE-Python [9]. For all the methods, the depth weighting parameter \( p \) in (5) was set to \( p = 0.8 \). The regions in the brain were discretized at 5 mm intervals.

VI. RESULTS AND DISCUSSION

Fig. 2 shows the localization error for the dipole source in the rA1 when varying the regularization parameter \( \lambda \). Table I shows the localization error and the value of \( \lambda \) for the smallest error. Also, the localization error of Deep Prior for \( \lambda = 0 \) (no depth weight) is shown in Table I. As shown in these results for the rA1, the localization error of Deep Prior with depth weighting was almost the same as that of sLORETA when setting an appropriate \( \lambda \). The estimated current distribution is shown in Fig. 3, where the actual current source was placed in the rA1. As shown in Fig. 3, when \( \lambda = 0 \), the current distribution estimated by Deep Prior was distributed at shallow locations in the brain. On the other hand, the current distribution estimated by Deep Prior with an appropriate \( \lambda \) was centered on the location of the actual current source.

Fig. 4 shows the localization error of the estimated current source when varying the regularization parameter \( \lambda \), where the actual current source was placed in the rV1. Table II shows the localization error and the value of \( \lambda \) when the smallest localization error was obtained for each method and \( \lambda = 0 \) for Deep Prior. As shown in Table II, in the case of the rA1

| Method   | \( \lambda \) | Localization Error [mm] |
|----------|---------------|--------------------------|
| MNE      | 0.44          | 18.9                     |
| sLORETA  | 0.22          | 2.5                      |
| DP-Dec   | 0             | 13.7                     |
| DP-UNet  | 0             | 13.7                     |
| DP-Dec   | 0.88          | 3.4                      |
| DP-UNet  | 0.88          | 3.4                      |

| Method   | \( \lambda \) | Localization Error [mm] |
|----------|---------------|--------------------------|
| MNE      | 4.1           | 29.7                     |
| sLORETA  | 4.1           | 1.8                      |
| DP-Dec   | 0             | 18.6                     |
| DP-UNet  | 0             | 18.6                     |
| DP-Dec   | 4.1           | 4.2                      |
| DP-UNet  | 1.3           | 4.2                      |
as well, by setting an appropriate $\lambda$ the localization errors of MNE and Deep Prior were reduced compared to the case when $\lambda = 0$. However, the localization errors of MNE and Deep Prior tended to be larger than that of the rA1. This may be due to the fact that the rV1 is located at a deeper position than the rA1, and the SNR of MEG data generated from the source in the rA1 was lower than the SNR of MEG data generated from the source in the rV1.

Fig. 2 and Fig. 4 indicate that the current norm regularization with depth weighting improves MEG source localization using Deep Prior by setting appropriate $\lambda$ depending on the location of the true current source. A larger $\lambda$ may be preferred for a deeper current source. However, increasing $\lambda$ also regularizes the current norm, resulting in a bias toward the surface and a large error in the MEG sensor space. It is necessary for more accurate estimation to adjust not only $\lambda$ but also $p$ in (5).

The performance of the current source estimation using Deep Prior with the U-Net architecture was almost the same as the performance of the estimation with the decoder architecture. In Deep Image Prior, the U-Net architecture including an encoder-decoder structure and skip connections is considered effective in modeling a natural image [6]. However, the current densities assumed in this study did not have complex structures like natural images. The decoder architecture may be adequate for modeling current density in the brain.

VII. CONCLUSIONS

In this work, in order to improve the performance of current source estimation using Deep Prior, we introduced regularization with depth weighting in Deep Prior. In our experiments, the MEG data synthesized by assuming a single current source in the rA1 and the rV1 were used, and the results showed that by setting appropriate regularization parameters, the localization error reduced and the current source was able to be estimated around the true position. Since the estimation is not yet satisfactory for deeper current sources, it is necessary to investigate the effect of other parameters $p$ and how to select optimal parameters. The evaluation of the proposed method on a wider variety of current sources is also an issue for future work.

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