Deep Learning for Cortical Potential Imaging

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Abstract. Electroencephalography (EEG) is a well-established non-invasive technique to measure the brain activity, albeit with a limited spatial resolution. Variations in electric conductivity between different tissues distort the electric fields generated by cortical sources, resulting in a smeared potential measurements on the scalp. One needs to solve an ill-posed inverse problem to recover the original neural activity. In this article, we present a generic methodology of recovering the cortical potentials from the EEG measurement by introducing a new inverse-problem solver based on deep convolutional neural networks (CNN) in a U-Net configuration. The solver was trained on a paired dataset from a synthetic head conductivity model by solving the diffusion equations with the finite element method (FEM). This is the first method that provides robust translation of EEG data to the cortex surface using deep learning. Supplying a fast and accurate interpretation of the tracked EEG signal, the proposed approach is a candidate for future non-invasive brain-computer interface devices.

Keywords: EEG · inverse problem · CNN · deep learning · FEM · cortex potential · brain mapping · neuroimaging · EEG super-resolution

1 Introduction

Electroencephalography (EEG) is a common method of non-invasive registration of the brain activity. It has high temporal resolution and is very inexpensive to own and to practice. These aspects make the adoption of EEG widespread, ranging from the areas of neurophysiological and cognitive research to non-invasive brain-computer interface (BCI) devices, to clinical studies, to diagnostics. However, there are multiple technical limitations to modern EEG technology, with a poor spatial resolution being the major one [17, 25]. The low spatial resolution of EEG is primarily caused by the significant difference of conductivity between the skull and the other tissues. Generally speaking, the conductivity of all tissues composing the head should be taken into account.

In this work, we will consider how to recover the signal from the brain given the measurement on the scalp, using the most recent arsenal of techniques from the classical and the deep learning disciplines. We proceed with a formal problem statement and with a review of the state-of-the-art.

1.1 Statement of the problem

Let the head be represented by the computational domain $\Omega \subset R^3$ bounded by a piecewise-smooth boundary $\partial\Omega$. Within the domain, the electric potential $p(\mathbf{x})$ satisfies the following expression [4]:

$$\nabla \cdot (\sigma(\mathbf{x})\nabla p(\mathbf{x})) = \nabla \cdot \mathbf{J}(\mathbf{x}) \text{ in } \Omega, \quad \mathbf{n}(\mathbf{x}) \cdot \nabla p(\mathbf{x}) = 0 \text{ on } \partial\Omega \tag{1}$$

where $\sigma(\mathbf{x})$ is the conductivity distribution over the head volume, $\mathbf{J}(\mathbf{x})$ represents the volumetric distribution of a primary current source that produces the signal, and $\mathbf{n}(\mathbf{x})$ is the vector normal to the surface $\partial\Omega$ at the point $\mathbf{x} \in \partial\Omega$. The conductivity σ is assumed to be known. We also introduce the area of measurements $\Gamma \subset \partial\Omega$, and the cortex $C \subset \Omega$. Based on equations (1), we can formulate three main mathematical problems (see Fig. 1 for visualizing the concept):
Forward problem (FP): *compute the scalp voltages $p(\mathbf{x})$, $\mathbf{x} \in \partial\Omega$, given current dipoles or density $\mathbf{J}(\mathbf{x})$.*
Inverse problem 1 (IP1): *given known electric voltages $p(\mathbf{x})$, $\mathbf{x} \in \Gamma$ on the area of measurements Γ, compute current density $\mathbf{J}(\mathbf{x}), \mathbf{x} \in C$ on the cortex.*
Inverse problem 2 (IP2): *given known electric voltages $p(\mathbf{x}), \mathbf{x} \in \Gamma$ on the area of measurements Γ, compute the electric voltage $p(\mathbf{x}), \mathbf{x} \in C$ on the cortex.*

State-of-the-art. The majority of algorithms proposed in the EEG community are dedicated to IP1 and formulated in the framework of Tikhonov regularization, including the MNE and LORETA families, etc. (see [10, 21, 20] for review). The main limitation of these methods is the sensitivity of their spatial resolution to the head model geometry and the high demand for computational resources (especially, if MRI-based head models are used). There are algorithms for solving IP2 [2, 8, 13] but their spatial resolution is still insufficient.

Recent studies propose neural networks as alternative method of the inverse problem solutions [12, 26]. Convolutional neural networks (CNN) are capable of providing both an approximation of the physical model and a sufficient regularization, leading to more accurate inverse-problem solution stable with respect to noisy inputs. U-Net can serve as an efficient integrator of various numerical modelling solutions to improve the accuracy [16]. An Autoencoder-based CNN was also proposed for EEG super-resolution as a non-linear interpolation method [14]. Finally, the most popular trend today is to use the temporal information as an additional constraint and to apply Markov models, or their approximations, in a recurrent network configuration (e.g. LSTM) [15, 11, 3].

In this work, we aspire to solve IP2 by the use of deep CNNs. We present a generic methodology for recovering cortical potentials (referred here as extended ECoG) from the EEG measurement using a new CNN-based inverse-problem solver in a simple U-Net configuration. Paired examples of EEG-ECoG synthetic data were generated via forward problem solving Eq. (1). Thus, we reformulate the problem as an image-to-image translation task and find a way to reconstruct accurate mapping of the cortical potentials to recover the original brain activity beyond the spatial resolution of EEG.

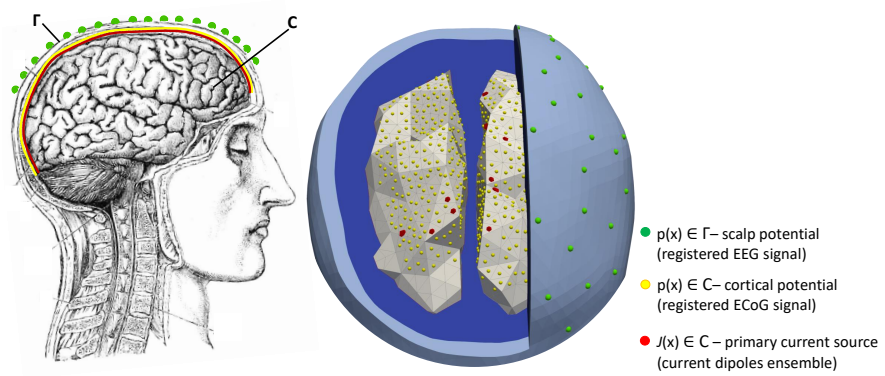


Fig. 1. General concept of cortical activity registration (left) and its physical model implemented in FEM (right). Image on the left side is reproduced from [5].

2 Methods

Head Model and Data Generation. A realistic 3-D head model was used to prepare a synthetic dataset (Fig. 1, right). An anatomical head model was constructed from the sample subject data of the `MNE` package [9]. We extracted triangulated surfaces of the cortex, skull and skin and smoothed them using the `iso2mesh` toolbox [23]. The volume conductor was meshed into 261,565 tetrahedrons with 42,684 vertices. The conductivity of the cortex surface, the skin, and the skull were assumed to be 0.33 S/m, 0.33 S/m, and 0.01 S/m, respectively [7].

Source current dipoles were positioned in the centers of the boundary triangles of the cortex mesh. For simplicity, we considered only the upper part of the cortex in order to provide an intuitive 2-D representation of the data, resulting in 400 possible locations of the source current dipoles (the number of active dipoles was, however, restricted for each simulation to n dipoles, as described below). Cortical potential sensors were located in the same manner, leading to 400 measurement probes of the cortex potential (see yellow dots in Fig. 1). Scalp potential sensors (i.e., channels of an EEG device) were located on the outer scalp surface according to the 10-20 system [27]. We also wanted to study different number of EEG channels: 128, 64, or 32.

Our simulation run went as follows. First, a random initialization of n current dipoles with the current values in the range 0.1-0.9 μA [19] was done. Then, we carried out a calculation of EEG and ECoG data as a numerical solution to the problem (1), discretized with the finite element method [1]. The resulting system was solved with preconditioned conjugate gradient method [6]. After the EEG and the ECoG pairs were modelled, we converted them into the 256×256 float32 images to provide precise topographic representation of the measured activity. Min-max contrast normalization was applied to the image intensities. Thus, each computed output is a pair of the top-view image of the scalp potential distribution and the top view image of the cortical potential distribution.

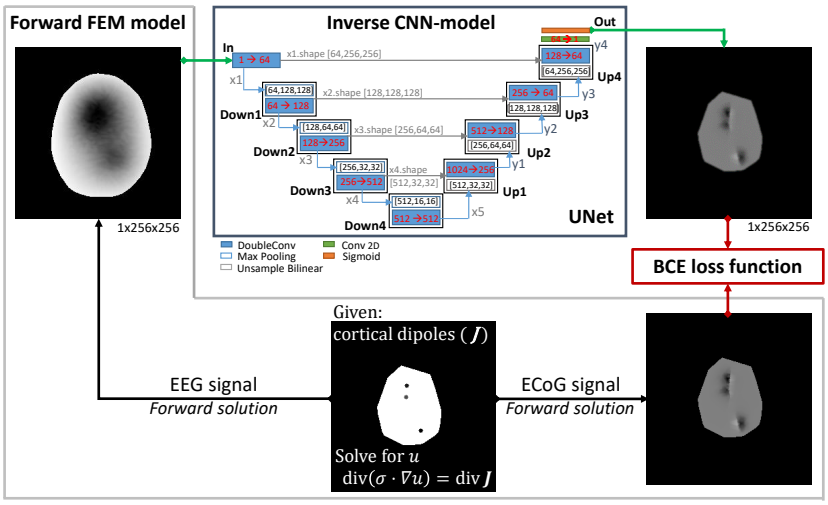


Fig. 2. U-Net-solver for imaging cortical potential from the EEG data. The EEG and the cortical potential (extended ECoG) images are modelled via solution to the forward problem (FP), defined in text.

Evaluation details. Using the head model, a dataset of synthetic EEG-ECoG pairs was generated. It was split into 5000 train, 400 validation, and 600 test pairs. Both the data generation and the training of the neural network were performed on the ZHORES supercomputer using Tesla V100-SXM2 GPUs [29].

To train the topographic translation from EEG to Cortical potential (ECoG) domain, we did minimal modifications to U-Net [24] (see Fig. 2) to adopt it to the paired image-to-image translation task. The U-Net network was optimized to minimize the Binary Cross Entropy (BCE) loss function between the recovered ECoG image and the corresponding ground truth (GT) ECoG image. The training was performed with the ADAM optimizer, sigmoid activation function, the batch size of 4, and the learning rate of 10^{-4}.

3 Experiments

We tested the effectiveness and robustness of the proposed solver by varying the complexity of the pattern of cortical activity. For this purpose, the proposed model was trained on four datasets with different number of active dipoles. We started from a toy dataset where the corresponding ECoG and the EEG image representations were generated from a superposition of one, two, or three source current dipoles. Then, we gradually raised the model's complexity to 5-10, 10-25, and 25-45 active dipoles, respectively (see Fig. 3, top row).

As can be seen in the Fig. 3, the U-Net-solver is capable of recovering the original cortical potential distribution pattern given the indiscernible EEG data input. The relative error between the ground truth cortical potential distribution

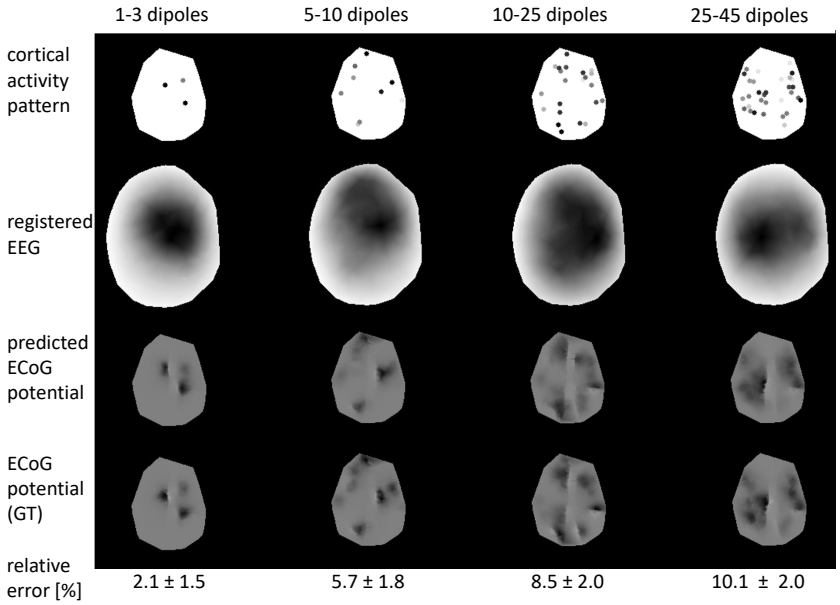


Fig. 3. U-Net-based solver results for cortical potential imaging as a function of a random number of randomly located source dipoles (columns from left to right correspond to the increased number of sources).

and the one obtained via the U-Net-solver is lower than 10%. The error does not change dramatically as the complexity of the original cortical activity pattern is varied.

We noted that the relative error dynamics can be explained not by the number of dipoles but by the variability of this parameter within the training set. In other words, when 1 to 3 dipoles are active simultaneously, the majority of the training examples is separable and the reconstruction of the sources lacks any ambiguity, but when the number of active dipoles rises to 10 to 25 dipoles, the separation of the source dipoles on the ground truth images is less pronounced. This additional ambiguity limits the overfitting of the solver.

To study the generalization performance of the U-Net-solver all trained models were reciprocally tested on all test sets. The experiments were done for the 128-channel EEG. We also tested the ability of the solver to process the EEG data, obtained from more commonly used EEG configurations (64 and 32 channels). For this experiment, pattern of only 5-10 dipoles were considered, and the result is shown in Fig. 4(inset table).

Conventional metrics, such as MAE and SSIM, were calculated for ECoG topomaps (background pixels were excluded). All cells in the tables of Fig. 4 are color-coded using empirical threshold: cells with relatively high performance (MAE<20 c.u. and SSIM>95%) are highlighted in green; cells with relatively

moderate performance (MAE<30 c.u. or SSIM>95%) are highlighted in yellow; the other cells are highlighted in red.

EEG-128			TRAIN			
			1-4 dipoles	5-10 dipoles	10-25 dipoles	25-45 dipoles
TEST	1-4 dipoles	MAE [*10³]	**3.7 ± 2.6**	6.8 ± 2.8	11.1 ± 3.8	31.9 ± 28.2
		SSIM [%]	**99.6 ± 0.5**	99.3 ± 0.5	98.5 ± 0.8	92.9 ± 7.5
	5-10 dipoles	MAE [*10³]	15.5 ± 6.4	**13.3 ± 4.2**	16.9 ± 4.4	23.7 ± 5.8
		SSIM [%]	97.3 ± 1.5	**97.8 ± 1.1**	97.3 ± 1.1	96.4 ± 1.1
	10-25 dipoles	MAE [*10³]	31.8 ± 10.8	24.6 ± 8.2	**23.0 ± 5.5**	26.8 ± 5.4
		SSIM [%]	94.2 ± 2.4	95.4 ± 1.9	**95.6 ± 1.5**	95.2 ± 1.4
	25-45 dipoles	MAE [*10³]	49.3 ± 13.9	38.0 ± 11.9	29.7 ± 7.6	**28.9 ± 5.3**
		SSIM [%]	91.3 ± 2.5	93.2 ± 2.3	94.3 ± 1.8	**94.5 ± 1.4**

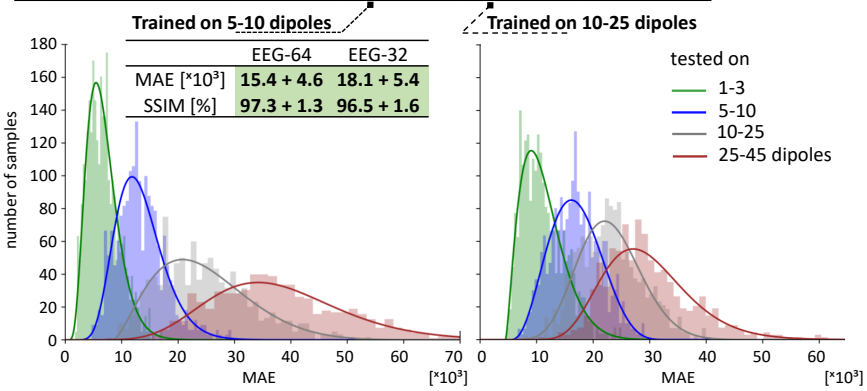


Fig. 4. Performance of U-Net-solver as a function of a number of active dipoles and a number of EEG channels. Cells, where both the train and the test data were generated with the same number of dipoles and the same number of channels, are marked in bold. Histograms on the bottom show MAE distribution with respect to the data used as the test sample; models were trained with 5-10 (left) and 10-25 (right) dipoles.

We observe that the U-Net-solver is capable of generalizing the input data and, thus, it effectively resolves the EEG signal even if the configuration differs from the source pattern which the solver was trained on. The trade-off between the solver's accuracy and its ability to generalize is demonstrated in the histograms (Fig. 4, bottom panel).

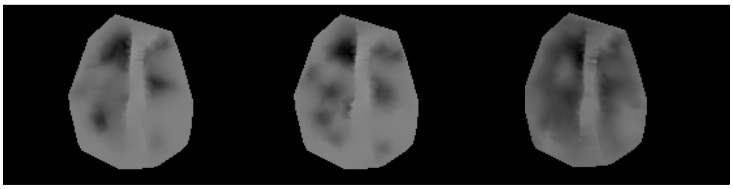
Hence, the solver has a better ability to process unseen data when it was trained on a dataset with more variability. However, it does not hold for the model trained on the most complicated data examples: e.g., ECoG patterns from a superposition of 25-45 dipoles is reconstructed more coarsely and the pre-trained solver fails to resolve the simpler data examples. This is possibly caused by the loss of information incurred by inaccurately representing the complex cortical patterns as 2D images instead of 3D volumes.

In contrast, the U-Net-solver effectively deals with EEG data in any available data configuration. The reduction of information in the input data recorded with 32 or 64 EEG channels (instead of 128 full channel set) does not significantly alter the efficiency of the U-Net-solver, as seen in the extended column 2 of the table in Fig. 4.

In the final experiment we compared the U-Net-solver with solutions of the Cauchy problem by the method of quasi-reversibility [13]. We used the same input for the two solvers, and adjusted their output in order to allow for their comparison (see Fig. 5A).

The same set of 128 EEG-channel data with 5% Gaussian noise was taken as input images for the U-Net-solver and the numerical solution to the Cauchy problem. The statistics calculated on 25 test samples (5-10 dipoles superposition) is shown in the table insets of Fig. 5.

A



Ground Truth	U-Net-solver	numerical solution
relative error [%]	6.1 ± 0.9	28.3 ± 2.35
MAE [$^{\times}10^{3}$]	13.2 ± 1.6	116.7 ± 10.4
SSIM [%]	97.7 ± 0.7	85.9 ± 1.8
PSNR [dB]	30.9 ± 1.2	17.5 ± 0.7

B

	SNR=10%	SNR=15%	SNR=20%	SNR=25%	SNR=30%
MAE [$^{\times}10^{3}$]	17.7 ± 5.8	21.3 ± 6.4	24.7 ± 7.3	27.4 ± 7.4	28.4 ± 7.4
SSIM [%]	96.6 ± 1.6	95.6 ± 1.8	94.4 ± 2.1	93.3 ± 2.3	92.2 ± 2.5
PSNR [dB]	29.5 ± 2.8	27.8 ± 2.4	26.6 ±2.3	25.8 ± 2.1	25.3 ± 2.0

Fig. 5. A. Comparison of our U-Net-solver against the numerical solution of the Cauchy problem by the method of quasireversibility [13]. The GT cortical potential distribution (left), the distribution recovered by the U-Net-solver (middle) and the numerial solution (right) results are shown in the top row. We can observe that the method of quasireversibility does not provide sufficient resolution to restore original pattern of the cortical activity. **B.** In order to estimate the stability of U-Net-solver we gradually increased the noise and estimated the error and the image quality scores.

The comparison in Fig. 5 shows the superiority of the U-Net-solver over the numerical methods, making our approach very promising for non-invasive cortical potential measurement. By nature of any numerical solution to an ill-posed

problem, one requires explicit regularization in order to stabilize its approximation, leading to an increase in error regardless of the numerical method. On the contrary, the proposed approach relies on neural networks that provide implicit regularization of the solution and, ultimately, yield superior accuracy. We also observe that the quality of the solution decreases linearly as the data noise is increased. The error dynamics suggests that our solution is more stable than those reported in [13].

Although our approach proved efficient in reconstructing unseen ECoG patterns, it requires paired EEG-ECoG datasets for training. Therefore, further, the development will be directed to unpaired image-to-image translation methods such as DualGAN [28, 22]. Another area of further research is the extension of our approach to translation between 3-D volumes [18], thus avoiding the loss of information caused by projection.

4 Conclusions

We proposed a new approach to brain activity reconstruction by reformulating it in an image-to-image translation framework and demonstrated mapping of the EEG data to the cortical potentials on the synthetic head model. CNN fine-tuned to directly approximate the inverse-operator, achieved a remarkably low error of reconstruction and high image quality scores, effectively promising a boost to the spatial resolution of the future EEG devices. The CNN-based solver demonstrated high stability with respect to noise and to the number of measurement inputs (EEG channels). Due to the flexibility of the solver, it can provide approximations to the solution regardless of the geometries of the scalp and the cortex that were used during training, potentially allowing high-accuracy image computing regardless of anatomical differences in different subjects. The trained U-Net-solver provides a fast and accurate prediction of the potentials of the distribution of sources on the cortex surface, which currently could be acquired only invasively in the clinical practice. We believe that this approach will be in demand in the areas where high-resolution and high-speed EEG data interpretation is sought after, for instance, in the non-invasive brain-computer interface devices.

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