Fast robust MEG source localization using MLPs

Sung Chan Jun, Barak A. Pearlmutter, and Guido Nolte
Department of Computer Science, University of New Mexico, Albuquerque, NM 87131, USA

Abstract

Source localization from MEG data in real time requires algorithms which are robust, fully automatic, and very fast. We present two neural network systems which are able to localize a single dipole to reasonable accuracy within a fraction of a millisecond, even when the signals are contaminated by considerable noise. The first network is a multilayer perceptron (MLP) which takes the sensor measurements as inputs, uses two hidden layers, and outputs source location in Cartesian coordinates. After training with random dipolar sources contaminated by real noise, localization of a single dipole could be performed within 300 microseconds on an 800 Mhz Athlon workstation, with an average localization error of 1.15 cm. To improve the accuracy to 0.28 cm, one can apply a few iterations of conventional Levenberg-Marquardt (LM) minimization using the MLP output as the initial guess. The combined method is about twenty times faster than multistart LM localization with comparable accuracy. In a second network with only one hidden layer, the outputs were the amplitudes of 193 evenly distributed Gaussian functions holding a soft distributed representation of the dipole location. We trained this network on dipolar sources with real noise, and externally converted the network's output into an explicit Cartesian coordinate representation of the dipole location. This new network had an improved localization accuracy of 0.87 cm, while localization time was lengthened to about 800 microseconds.

1 Introduction

There are a number of popular localization methods [1] most of which assume a dipolar source. Among them, the multilayer perceptron (MLP) [2] has been popular for building fast robust dipole localizers. In particular, fast dipole localizers are important in brain-computer interface systems. Since MLPs were first used for EEG dipole source localization and presented as feasible source localizers by Abeyratne *et al.* [3], various approaches using MLPs to localize sources of EEG or MEG signals have been attempted. Related works may be found in [4, 5] and references therein.

In this study we propose two MLPs which are able to localize a single dipole to reasonable accuracy from MEG signals contaminated by noise within a millisecond. The first network is a conventional Cartesian-MLP [5] which takes the sensor measurements as inputs, uses two hidden layers, and outputs the source location in Cartesian coordinates. The second network is a novel Soft-MLP with only one hidden layer, whose outputs are the amplitudes of evenly distributed Gaussian functions holding a soft distributed representation of the dipole location. An external decoder converts the network's output into an explicit Cartesian coordinate representation.

We use an analytical forward model of quasi-static electromagnetic propagation through a spherical head to map randomly chosen dipoles to sensor activities, and train MLPs to invert this mapping in the presence of real brain noise. A performance comparison of the Cartesian-MLP, the Soft-MLP, and a hybrid method—LM initialized by a MLP—are presented.

2 Methods

2.1 Data

Our synthetic data consisted of corresponding pairs of dipole locations and sensor activations, as generated by our forward model. Given a dipole location and a set of sensor activations, the minimum error dipole moment can be calculated analytically. Therefore, we discarded the moment in all the experiments below.

We made two datasets, one for training and the other for testing. Dipoles in the training and testing sets were drawn uniformly from truncated spherical regions, as shown in Figure 1. The dipole moments were drawn uniformly from vectors of strength $\leq$100 nAm. The corresponding sensor activations were the results of a forward model plus a noise model. To allow the network to interpolate rather than extrapolate, thus improving performance, the training set used dipoles from the larger region, while the test set contained only dipoles from the smaller inner region. We used a standard analytic forward model of quasistatic electromagnetic propagation in a spherical head [1, 6], with the sensor geometry of a 4D Neuroimaging Neuromag-122 gradiometer.

In order to properly compare the performance of localizers, we need a dataset for which we know the ground truth, but which contains the sorts of noise encountered in actual MEG recordings [5]. The real brain noise was taken from MEG recordings during periods in which the brain region of interest was quiescent. These signals were not averaged. The real brain noise has an RMS of roughly $P^n = 50$–100 fT/cm. We measured the S/N ratio of a dataset using the ratios of the powers in the signal and the noise: S/N (in dB) $= 10 \log_{10} P^{\mathrm{s}}/P^{\mathrm{n}}$ where P^{s} is the RMS (square root of mean square) of the sensor readings from the dipole and P^{n} is the RMS of the sensor readings from the noise. The dataset was made by adding real brain noise (without scaling) to synthetic sensor activations generated by the forward model and exemplars whose resulting S/N ratio was under 0 dB were rejected.

2.2 MLP structures

The Cartesian-MLP and the Soft-MLP charged with approximating the inverse mapping had an input layer of 122 units, one for each sensor. The Cartesian-MLP had two hidden layers with N_1 and N_2 units and an output layer of three units representing the dipole location (x, y, z). The Soft-MLP consists of one hidden layer with N units, and an output layer of 193 units representing the amplitudes of 193 uniformly distributed three-dimensional Gaussian functions in the training region of the head model [2].

These Gaussian functions are defined by

$$G_i(\mathbf{x}) = \exp\left(-\frac{|\mathbf{x} - \mathbf{x}_i|^2}{2\sigma^2}\right) \qquad \text{for } i = 1, \ldots, 193$$

where $\mathbf{x}_i$ is a center of Gaussian function and σ is a fixed width parameter. These Gaussian functions are homogeneously distributed with adjacent centers at a distance 3 cm and a width parameter $\sigma = 1.8$ cm. The decoding strategy to convert the activations into a Cartesian coordinate representation was:

- For the 193 output values $(a_i \approx G_i(\mathbf{x}))$, find the index i^* of maximum amplitude $i^* = \arg\max_i a_i$.
- For some neighborhood I of $\mathbf{x}_{i^*}$, estimate the dipole location by linear interpolation,

$$\hat{\mathbf{x}} = \frac{\sum_{\mathbf{x}_i \in I} a_i \mathbf{x}_i}{\sum_{\mathbf{x}_i \in I} a_i}.$$

Output units had linear activation functions, while to accelerate training hidden units used the hyperbolic tangent activation function [7]. All units had bias inputs, adjacent layers were fully connected, and there were no cut-through connections, which is shown in Figure 2. The 122 MEG sensor activations were scaled so that their RMS value was 0.5. The network weights were initialized with uniformly distributed random values in ± 0.1. Backpropagation was used to calculate the gradient, and online stochastic gradient decent for the optimization. No momentum was used, and learning rate was chosen empirically.

To empirically determine the number of hidden units, we trained two MLPs with various numbers of hidden units and we measured the tradeoff between approximation accuracy and computation time. Finally, we chose 122–60–30–3 and 122-80-193 as the Cartesian-MLP size and the Soft-MLP size, respectively.

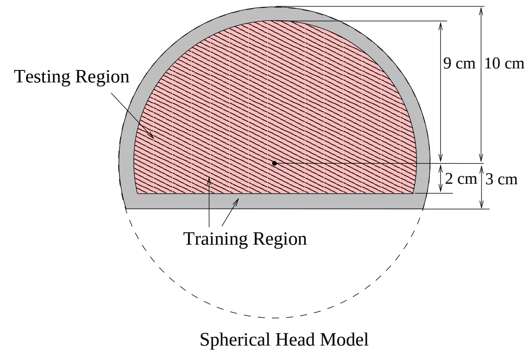

Figure 1: Training and testing regions for a spherical head model.

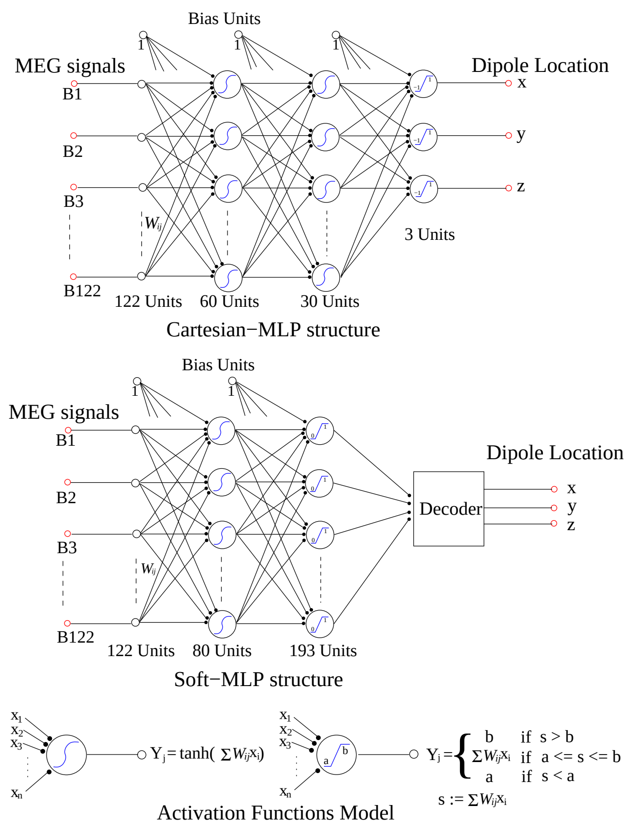

Figure 2: Training dataset was trained in these Cartesian-MLP and Soft-MLP structures.

3 Results

We trained two MLPs with the same brain noise training dataset of 20,000 exemplars, and 4,500 MEG signal patterns contaminated by real brain noise were tested. We used up to 500 epochs which took four to twelve hours on an 800 MHz AMD Athlon to train each network. Each of the MLP localizers was used as an LM initializer, for the MLP-start-LM localizer. For the comparison of MLPs and their hybrid systems, LM was started with n randomly chosen restarts, which is called "random-n-start-LM." We checked how many restarts of LM were needed to match the accuracy of the hybrid systems. For the hybrid systems

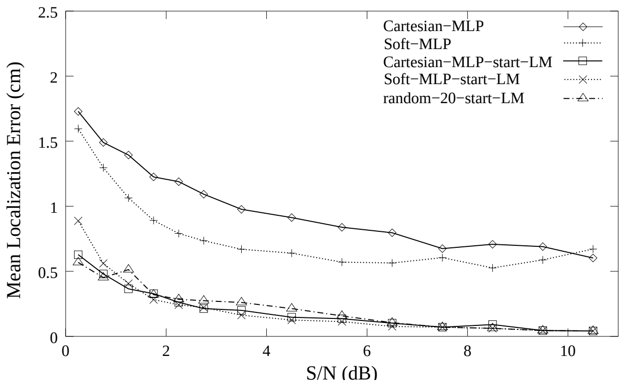

Figure 3: Mean localization error versus S/N for multistart LM, the Cartesian-MLP, the Soft-MLP and their hybrid methods.

algorithm	speed (ms)	accuracy (cm)
random-20-start-LM	2175.0	0.31
Cartesian-MLP	0.3	1.15
Soft-MLP	0.8	0.87
Cartesian-MLP-start-LM	36.0	0.28
Soft-MLP-start-LM	31.0	0.30

Table 1: Comparison of performance on real brain noise test set of LM, trained MLPs and hybrid systems for the Cartesian-MLP and the Soft-MLP structures. Each number is an average over 4,500 localizations.

over 20 restarts were required.

The performance of localization systems on two MLP structures, their variant hybrid MLP-start-LM localizers, and random-20-start-LM are shown as a function of S/N in Figure 3. As a whole, the Soft-MLP shows better localization performance than the Cartesian-MLP. At high S/N ratios the Soft-MLP-start-LM shows slightly better localization accuracy than the Cartesian-MLP-start-LM, but it is worse in accuracy at low S/N ratio signals.

A grand summary, averaged across various S/N conditions, is shown in Table 1. The localization error of the Soft-MLP decreases to 0.87 cm from 1.15 cm, while computation cost increases from 0.3 ms to 0.8 ms. The hybrid method of the Soft-MLP is slightly faster in computation time than that of the Cartesian-MLP, while both hybrid methods are comparable in localization accuracy. It is interesting to note that the initial guess of the Soft-MLP is close to the optimum, so the LM optimization needs fewer iterations.

4 Discussion

We presented the Cartesian-MLP and the Soft-MLP structures, which are able to localize a single dipole within a millisecond, presented their hybrid methods, and compared their performances. Experiments show that the Cartesian-MLP and Soft-MLP are feasible fast robust dipole source localizers. The Soft-MLP is more accurate than the Cartesian-MLP, at the expense of slightly greater computation time.

The hybrid methods, MLP-start-LM, are real time localizers which dramatically improve the localization accuracy beyond that of the original MLP. MLP-start-LM using the Soft-MLP is slightly faster than, and comparable in accuracy to, MLP-start-LM using the Cartesian-MLP.

Acknowledgements

Supported in part by NSF CAREER award 97-02-311, the National Foundation for Functional Brain Imaging, and a gift from the NEC Research Institute.

References

[1] M. Hämäläinen, R. Hari, R. J. Ilmoniemi, J. Knuutila, and O. V. Lounasmaa, "Magnetoencephalography — theory, instrumentation, and applications to noninvasive studies of the working human brain," *Reviews of Modern Physics*, vol. 65, pp. 413–497, 1993.

[2] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," in *Parallel distributed processing: Explorations in the microstructure of cognition, Volume 1: Foundations* (D. E. Rumelhart, J. L. McClelland, and the PDP research group., eds.), MIT Press, 1986.

[3] U. R. Abeyratne, Y. Kinouchi, H. Oki, J. Okada, F. Shichijo, and K. Matsumoto, "Artificial neural networks for source localization in the human brain," *Brain Topography*, vol. 4, pp. 3–21, 1991.

[4] G. V. Hoey, J. D. Clercq, B. Vanrumste, R. V. de Walle, I. Lemahieu, M. D'Havé, and P. Boon, "EEG dipole source localization using artificial neural networks," *Phys. Med. Biol.*, vol. 45, pp. 997–1011, 2000.

[5] S. C. Jun, B. A. Pearlmutter, and G. Nolte, "Fast accurate MEG source localization using MLP trained with realistic noise," 2002. In Submission.

[6] J. C. Mosher, R. M. Leahy, and P. S. Lewis, "EEG and MEG: Forward solutions for inverse methods," *IEEE Transactions on Biomedical Engineering*, vol. 46, pp. 245–259, 1999.

[7] Y. LeCun, I. Kanter, and S. A. Solla, "Second order properties of error surfaces: Learning time and generalization," in *Advances in Neural Information Processing Systems 3*, pp. 918–924, Morgan Kaufmann, 1991.