EEG and MEG Inversion Using Convolutional and Recurrent Neural Networks

Joaquin J. Casanova, *Member, IEEE,* Zachary D. Stoecker-Sylvia, *Member, IEEE,*
Ryan Miyamoto, *Member, IEEE,* and Jenshan Lin, *Fellow, IEEE*

***Abstract*—Real-time localzation of neuronal activity has a number of uses, including brain-computer interfaces and medical diagnostics. Generally, this is done by taking measurements of the brain's magnetic and electric fields (magnetoencephalography [MEG] and electroencephalography [EEG]), and inverting the measurements. Most approaches are physically-based, and attempt to find the best estimate of the lead-field matrix, which relates the dipole activation to the field strength by minimizing the error of an estimate. To date, most approaches using the lead-field matrix are complicated and too slow in real time, aimed primarily at elucidating brain structural functional relationships from experimental data. We propose a new technique in which the location of peak neuronal current is estimated by treating EEG and MEG as a two-channel image, or time-series of images, which is processed by a neural network which returns the location of the dipole of peak magnitude. Four archtectures are tested: 2-layer perceptron, convolutional neural network (CNN), recurrent neural network (RNN), and CNN feeding RNN. In the absence of true measures of neuronal activity, we used two publicly available MEG/EEG datasets, and treated the estimates of the traditional minimum-norm estimate (MNE) as true estimates. We test the four variations of the network architecture, and in the best case (CNN only), we achieve test dataset errors (RMSE of max dipole location) of between XX and YY mm.**

***Index Terms*—EEG, MEG, Localization, Neural networks.**

I. Introduction

THERE is a great need for interpretation of brain signals for both use in control of devices, for prosthetics, for example, or for disease diagnostics . Sensor measurements include ... Problem of neuron localization or distribution of currents typical approaches our approach: max dipole

[1]

An MEG-based brain–computer interface (BCI)

[2]

The impact of EEG/MEG signal processing and modeling in the diagnostic and management of epilepsy

Inversion methods

[3]

Review on solving the inverse problem in EEG source analysis

[4]

Multiple dipole modeling and localization from spatio-temporal MEG data

[5]

Inverse localization of electric dipole current sources in finite element models of the human head

[6]

A solution to the dynamical inverse problem of EEG generation using spatiotemporal Kalman filtering

[7]

Non-stationary magnetoencephalography by Bayesian filtering of dipole models

[8]

Applications of the signal space separation method

[9]

Reconstructing spatio-temporal activities of neural sources using an MEG vector beamformer technique

[10]

EEG dipole source localization using artificial neural networks

Neural nets

[11]

Convolutional

[12]

Long short-term memory Recurrent

[13] Translating videos to natural language using deep recurrent neural networks

Data/processing [14]

II. Methods

1) Datasets: [14] Subsubsection text here. Audio Faces

A. Preprocessing

B. Description of Neural Networks

tensorflow.com [15]

Adam: A method for stochastic optimization

Subsection text here.

C. Hyperparameters

D. Training and testing

III. Results

IV. Conclusion

The conclusion goes here.

Acknowledgment

The authors would like to thank...

J. Casanova and J. Lin are with the Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL, 32611 USA e-mail: jcasa@ufl.edu

R. Miyamoto and Z. Stoecker-Sylvia are with Oceanit.

Manuscript received

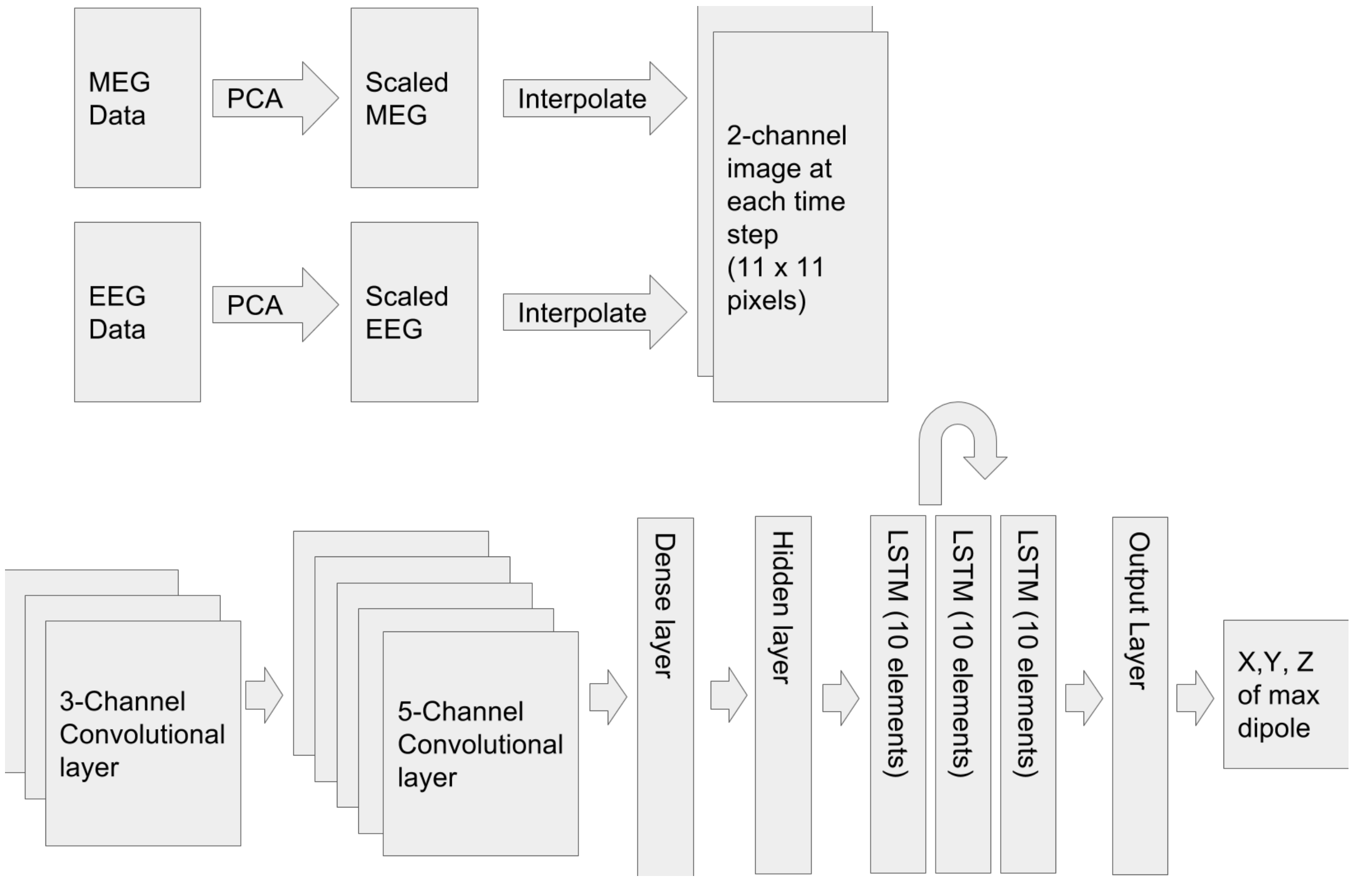

Fig. 1. Block diagram of CNN+RNN neural network.

References

[1] J. Mellinger, G. Schalk, C. Braun, H. Preissl, W. Rosenstiel, N. Birbaumer, and A. Kübler, "An meg-based brain–computer interface (bci)," *Neuroimage*, vol. 36, no. 3, pp. 581–593, 2007.

[2] F. H. L. da Silva, "The impact of eeg/meg signal processing and modeling in the diagnostic and management of epilepsy," *IEEE Reviews in Biomedical Engineering*, vol. 1, pp. 143–156, 2008.

[3] R. Grech, T. Cassar, J. Muscat, K. P. Camilleri, S. G. Fabri, M. Zervakis, P. Xanthopoulos, V. Sakkalis, and B. Vanrumste, "Review on solving the inverse problem in eeg source analysis," *Journal of neuroengineering and rehabilitation*, vol. 5, no. 1, p. 1, 2008.

[4] J. C. Mosher, P. S. Lewis, and R. M. Leahy, "Multiple dipole modeling and localization from spatio-temporal meg data," *IEEE Transactions on Biomedical Engineering*, vol. 39, no. 6, pp. 541–557, 1992.

[5] H. Buchner, G. Knoll, M. Fuchs, A. Rienäcker, R. Beckmann, M. Wagner, J. Silny, and J. Pesch, "Inverse localization of electric dipole current sources in finite element models of the human head," *Electroencephalography and clinical Neurophysiology*, vol. 102, no. 4, pp. 267–278, 1997.

[6] A. Galka, O. Yamashita, T. Ozaki, R. Biscay, and P. Valdés-Sosa, "A solution to the dynamical inverse problem of eeg generation using spatiotemporal kalman filtering," *NeuroImage*, vol. 23, no. 2, pp. 435–453, 2004.

[7] E. Somersalo, A. Voutilainen, and J. Kaipio, "Non-stationary magnetoencephalography by bayesian filtering of dipole models," *Inverse Problems*, vol. 19, no. 5, p. 1047, 2003.

[8] S. Taulu, J. Simola, and M. Kajola, "Applications of the signal space separation method," *IEEE transactions on signal processing*, vol. 53, no. 9, pp. 3359–3372, 2005.

[9] K. Sekihara, S. S. Nagarajan, D. Poeppel, A. Marantz, and Y. Miyashita, "Reconstructing spatio-temporal activities of neural sources using an meg vector beamformer technique," *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 7, pp. 760–771, 2001.

[10] G. Van Hoey, J. De Clercq, B. Vanrumste, R. Van de Walle, I. Lemahieu, M. D'Havé, and P. Boon, "Eeg dipole source localization using artificial neural networks," *Physics in medicine and biology*, vol. 45, no. 4, p. 997, 2000.

[11] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[12] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[13] S. Venugopalan, H. Xu, J. Donahue, M. Rohrbach, R. Mooney, and K. Saenko, "Translating videos to natural language using deep recurrent neural networks," *arXiv preprint arXiv:1412.4729*, 2014.

[14] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, R. Goj, M. Jas, T. Brooks, L. Parkkonen *et al.*, "Meg and eeg data analysis with mne-python," *Frontiers in neuroscience*, vol. 7, p. 267, 2013.

[15] D. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

PLACE
PHOTO
HERE

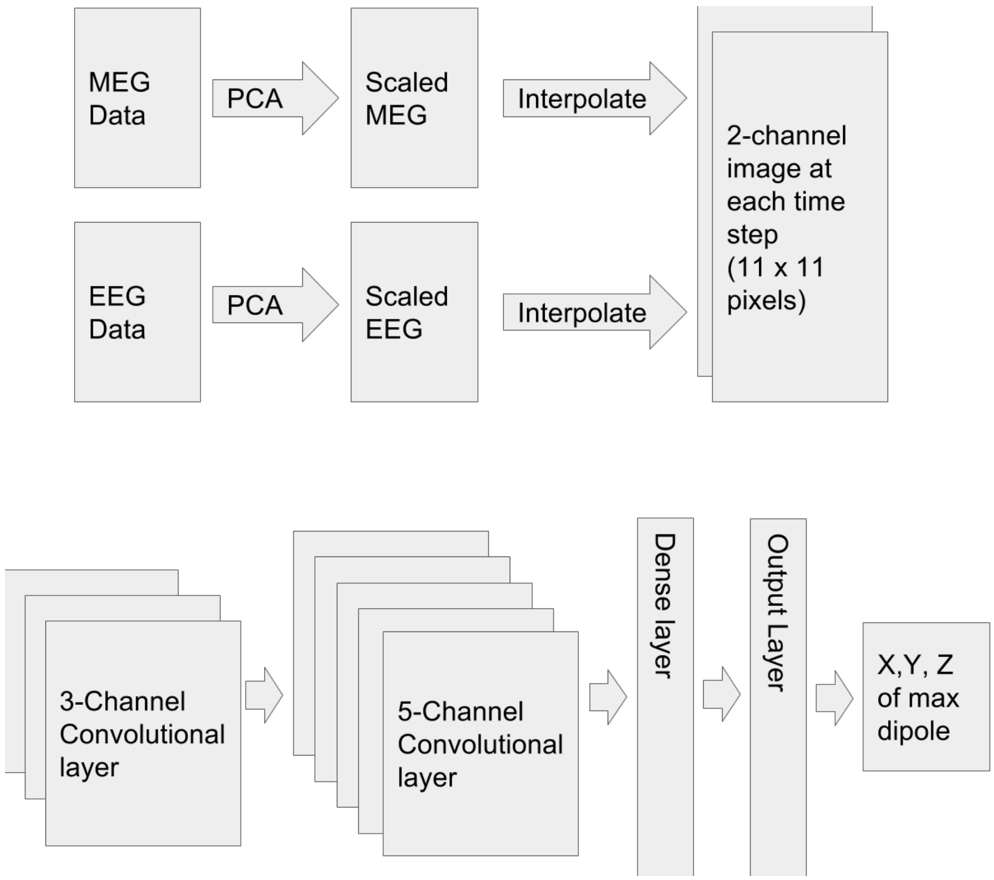

Fig. 2. Block diagram of CNN neural network.

Jane Doe Biography text here.

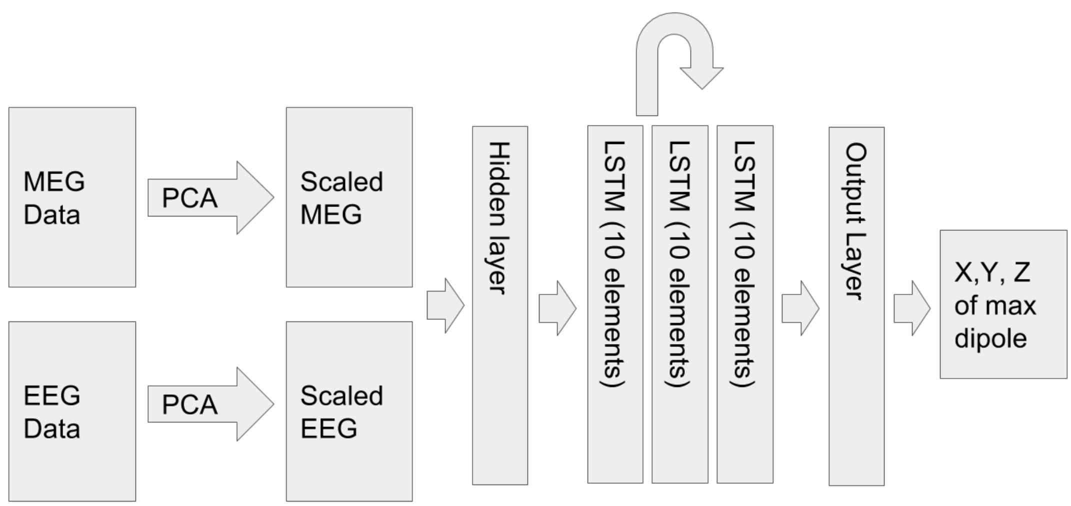

Fig. 3. Block diagram of RNN neural network.

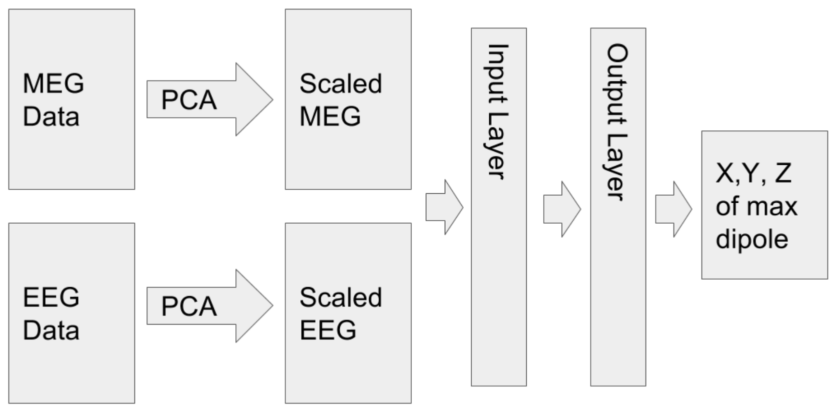

Fig. 4. Block diagram of MLP neural network.

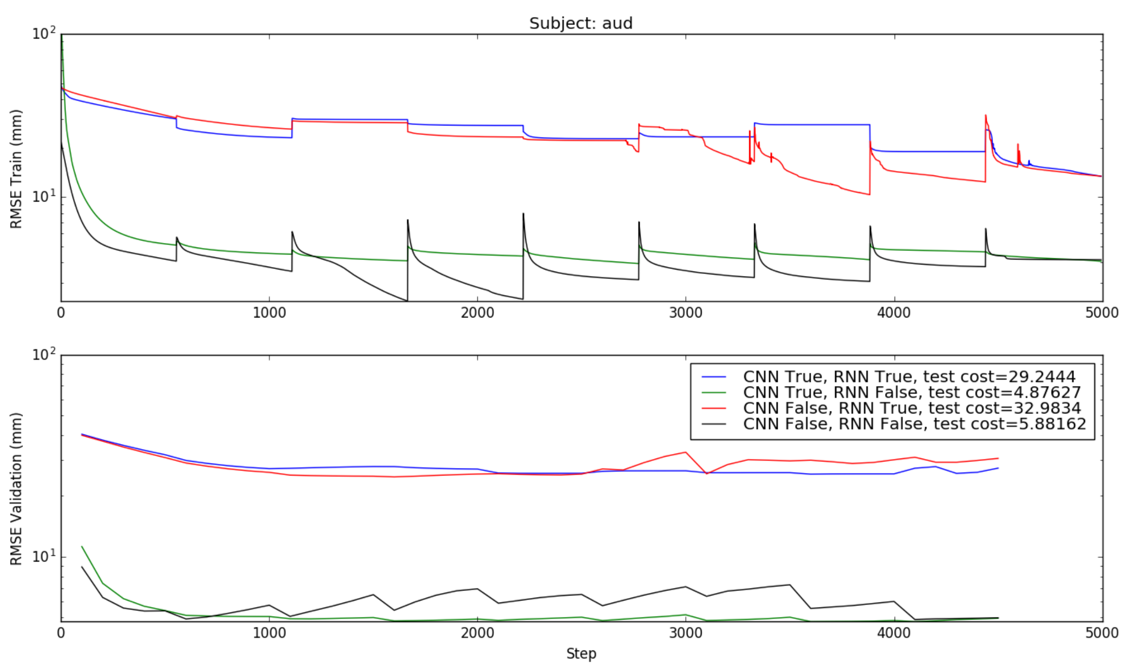

Fig. 5. Training/validation results for auditory stimulus dataset.

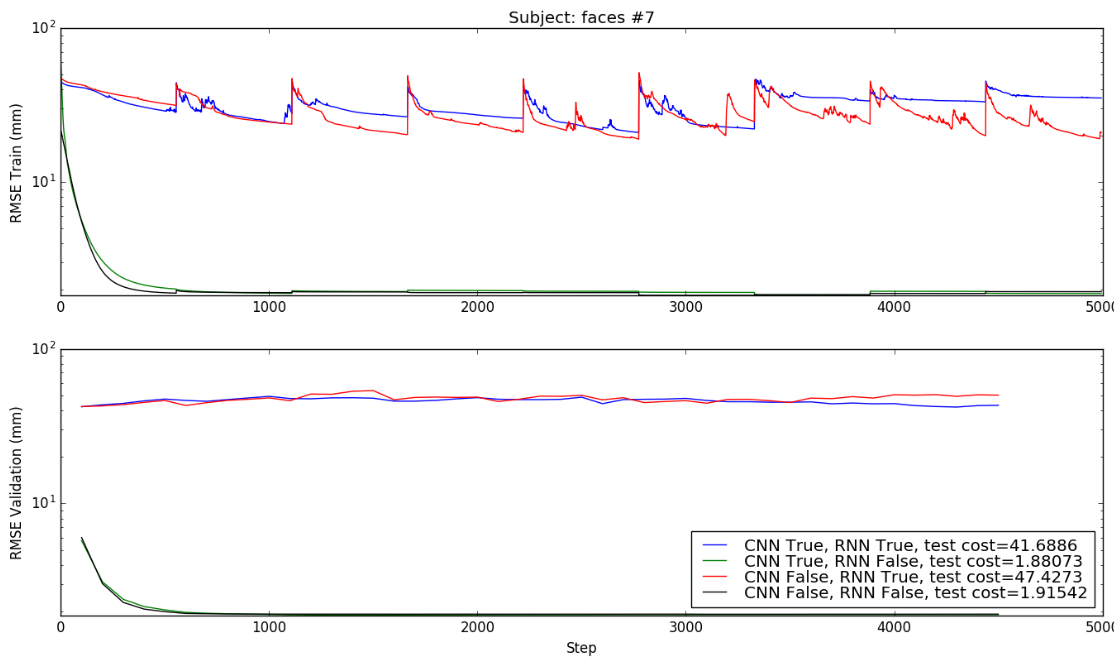

Fig. 6. Training/validation results for faces stimulus dataset.