EEG and MEG Inversion Using Convolutional and Recurrent Neural Networks

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***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. Magnetoencephalography (MEG), the measurement of the brain's magnetic field, is typically done using cryogenic superconducting quantum interference devices (SQUID) on a dense grid surrounding the skull, and has been used in brain-computer interfaces [1]. Additionally, electroencephalography (EEG), is also used for BCI as well as medical diagnostics and study of brain stucture and function [2]. Particularly for the latter, there is great utility in using the external measurements of MEG and EEG to determine which parts of the brain are most electrically active, a problem know as localization or inversion. Functional magnetic resonance imaging (fMRI) can be used but instead measures blood flow, and is thus not a direct measurement of electrical activity [3].

Classically, MEG/EEG inversion has followed one of a few approaches, with incremental enhancements as sophistication and computational power has increased. [4] provides an excellent review of techniques. [5] established the oroignal framework of the dipole in a sphere model, in which a lead-field matrix based on magnetostatic and electrostatic equations, and the positions of dipoles, transforms a vector of dipole magnitudes into a vector of magnetic flux and electric potential at sensor locations. The problem of localization becomes a problem of finding the locations and magnitudes of dipoles that minimize the square error of predicted versus observed fields. Using this formalism and a finite-element model, [6] localized dipoles from MEG data. [7] used Kalman filtering to solve the dynamical inverse problem. Thesignal-space separation method transforms the data into basis functions in signal space to better filter background noise sources [9]. Beamformer techniques have also been applied for MEG/EEG inversion [10]. More recently, EEG has been inverted using artificial neural networks [11].

Neural networks have proven an important tool for accurate predictions from noisy and large datasets. A recent technique is convolutional neural networks, in which image inputs are convolved with weighted kernels [12]. To treat time-series or sequences, recurrent neural networks, incorporating temporal feedback, have been developed, such as the long-short-term memory RNN [13]. CNN and RNN have been combined in [14] to translate video sequences into text descriptions of the video.

Our proposed idea is to apply the combined CNN/RNN framework to sequences of MEG/EEG data, and predict the location of only the peak dipole. In this way we simplify the problem, and with approporiately trained networks, we could make quick predicts from data, possibly in real time. To demonstrate our technique, we use publicly available datasets, and use the dipole currents predicted by a well established technique (MNE) as the true value to which we compare our estimates and train our network [15]. Further, we investigate four variations of the network architecture (2-layer MLP, RNN, CNN, and CNN with RNN), to establish the advantages and disadvantages of each.

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II. Methods

1) Datasets: [16] [17] Subsubsection text here. Audio Faces

A. Preprocessing

B. Description of Neural Networks

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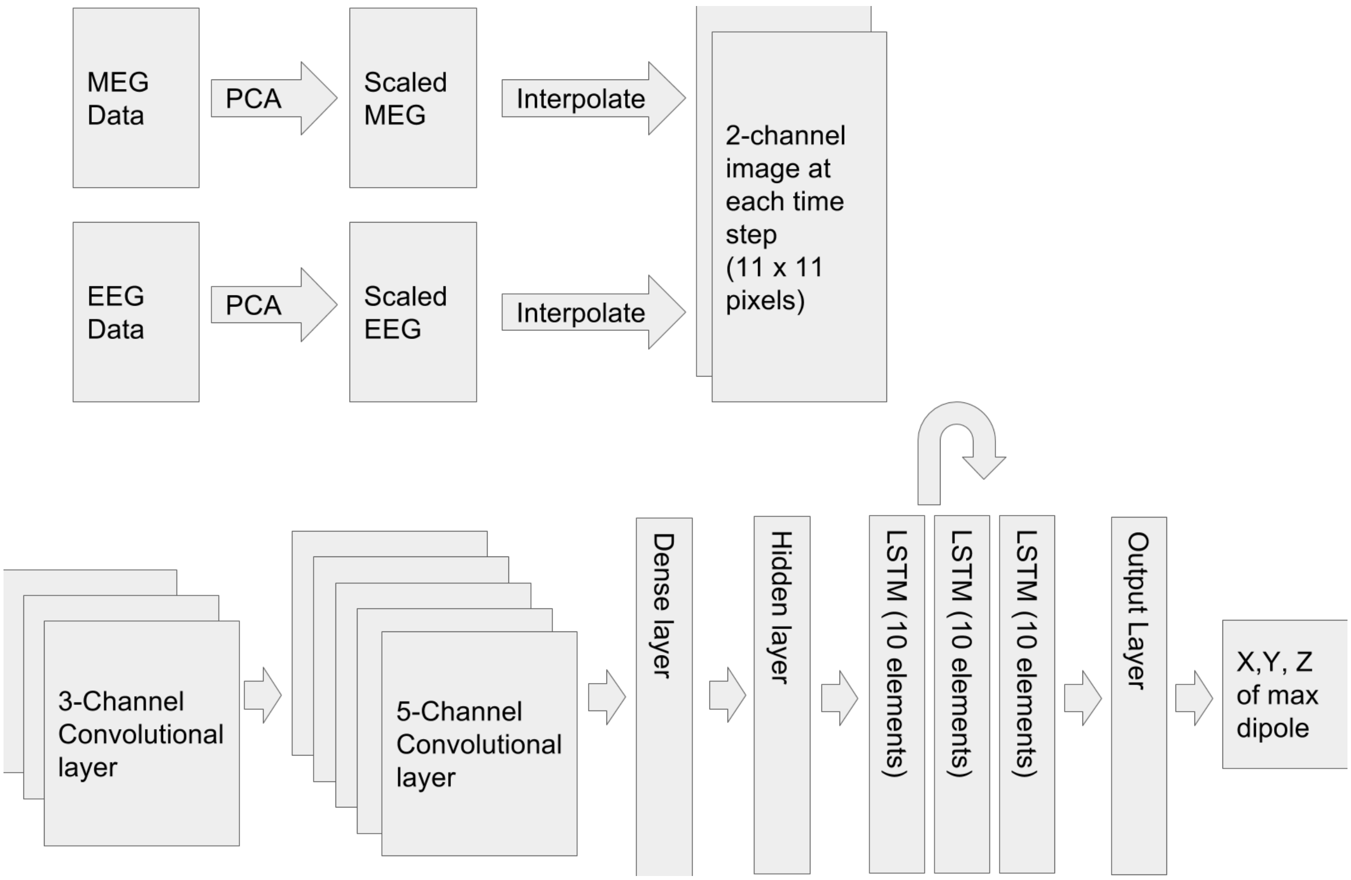

Fig. 1. Block diagram of CNN+RNN neural network.

C. Hyperparameters

D. Training and testing

III. Results

IV. Conclusion

The conclusion goes here.

Acknowledgment

The authors would like to thank...

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] D. Sharon, M. S. Hämäläinen, R. B. Tootell, E. Halgren, and J. W. Belliveau, "The advantage of combining meg and eeg: comparison to fmri in focally stimulated visual cortex," *Neuroimage*, vol. 36, no. 4, pp. 1225–1235, 2007.

[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

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

[14] 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.

[15] A. Gramfort, M. Luessi, E. Larson, D. A. Engemann, D. Strohmeier, C. Brodbeck, L. Parkkonen, and M. S. Hämäläinen, "Mne software for processing meg and eeg data," *Neuroimage*, vol. 86, pp. 446–460, 2014.

[16] D. G. Wakeman and R. N. Henson, "A multi-subject, multi-modal human neuroimaging dataset," *Scientific data*, vol. 2, 2015.

[17] 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.

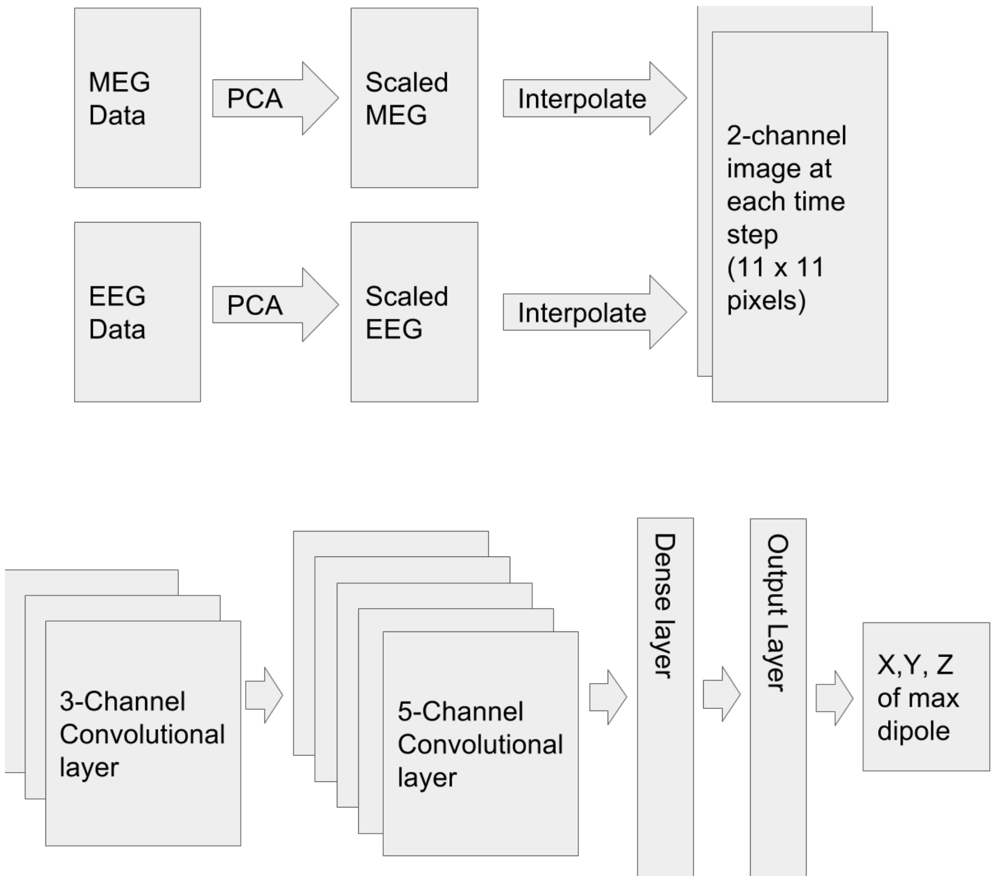

Fig. 2. Block diagram of CNN neural network.

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

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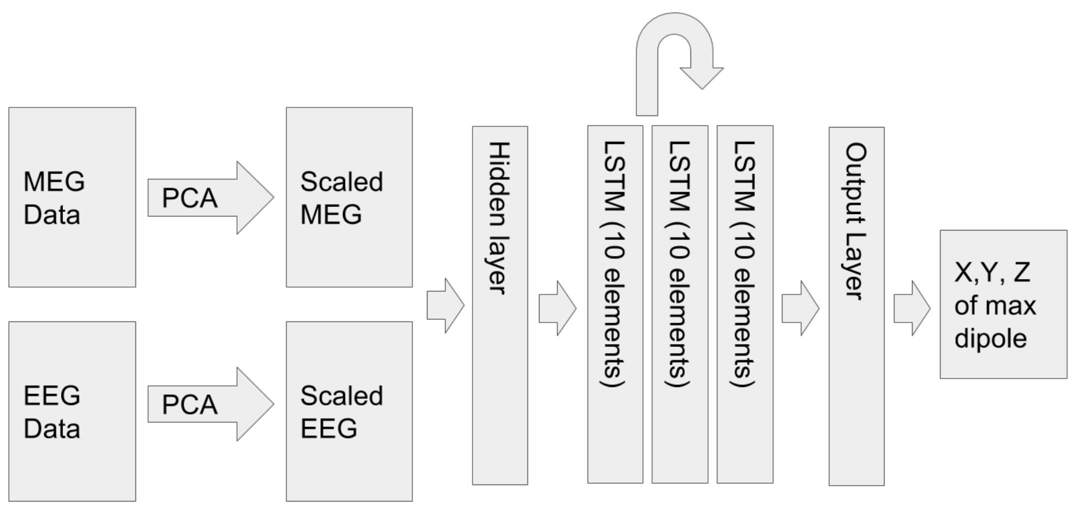

Fig. 3. Block diagram of RNN neural network.

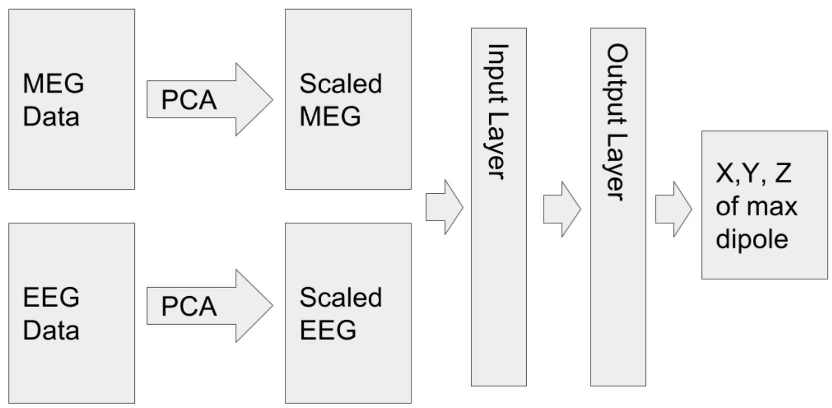

Fig. 4. Block diagram of MLP neural network.

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

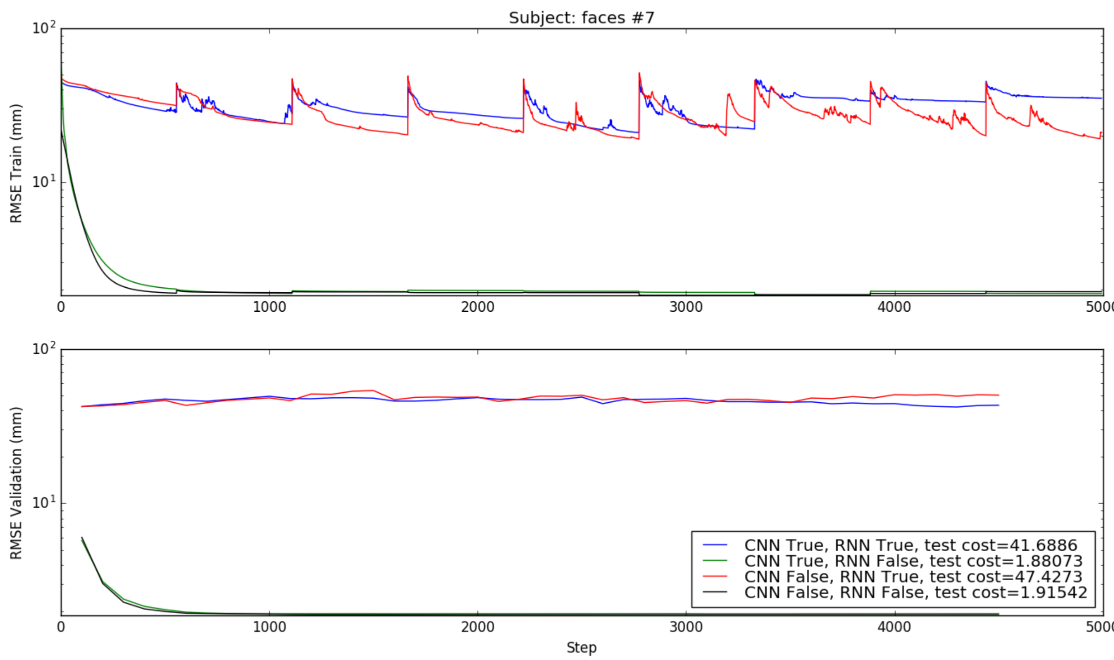

Fig. 6. Training/validation results for faces stimulus dataset.