EEG and MEG Inversion Using Convolutional and Recurrent Neural Networks

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***Abstract*—BCI, diagnostics - localize neural activity Measurement techniques dense sensors Average acros trials Typical inversion approach Our approach more simplified CNN/RNN/MLP Test data sets evaluate architectures for error and ability to generalize after training Key results**

***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

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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...

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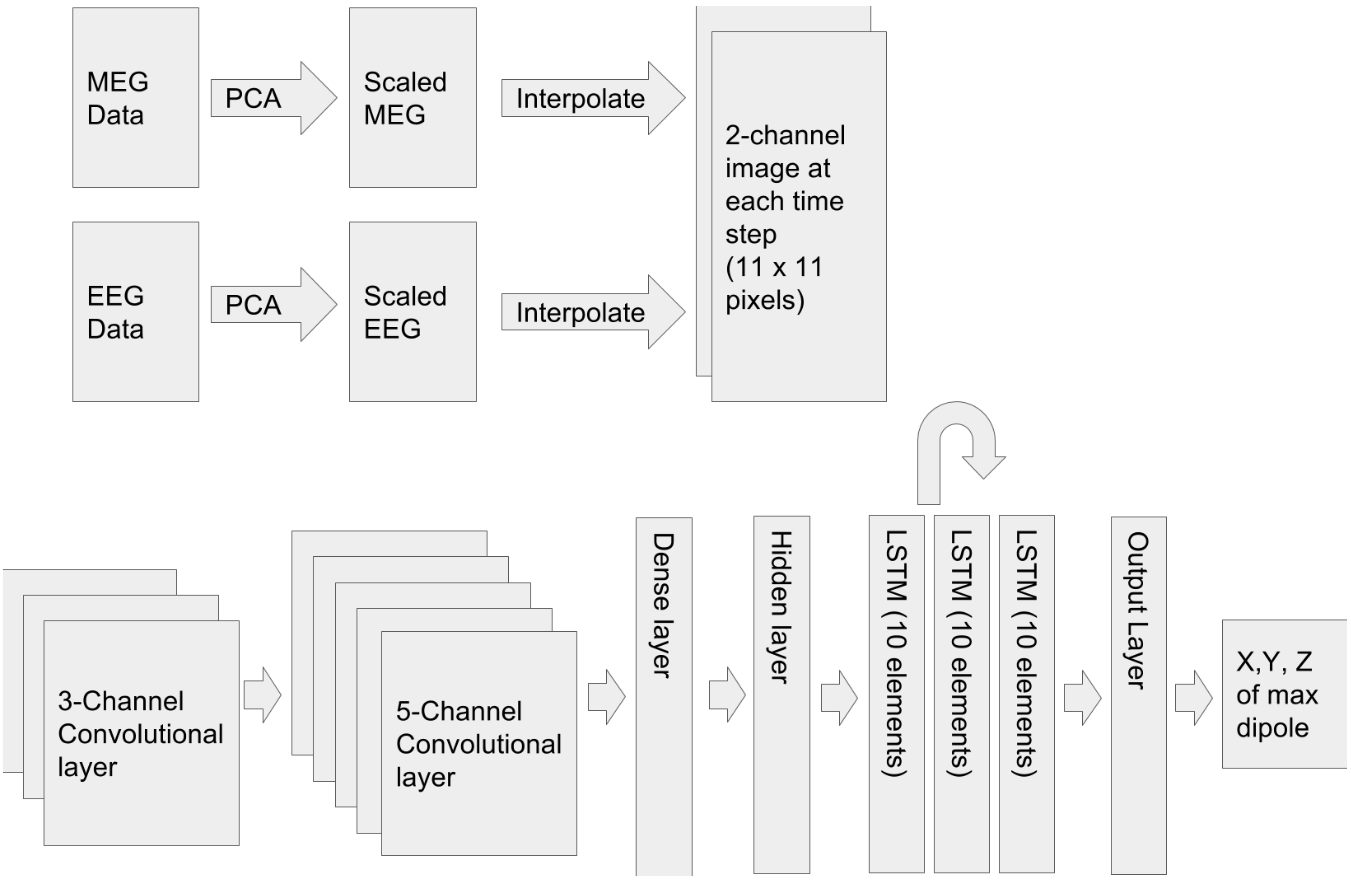

Fig. 1. Block diagram of CNN+RNN neural network.

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Jane Doe Biography text here.

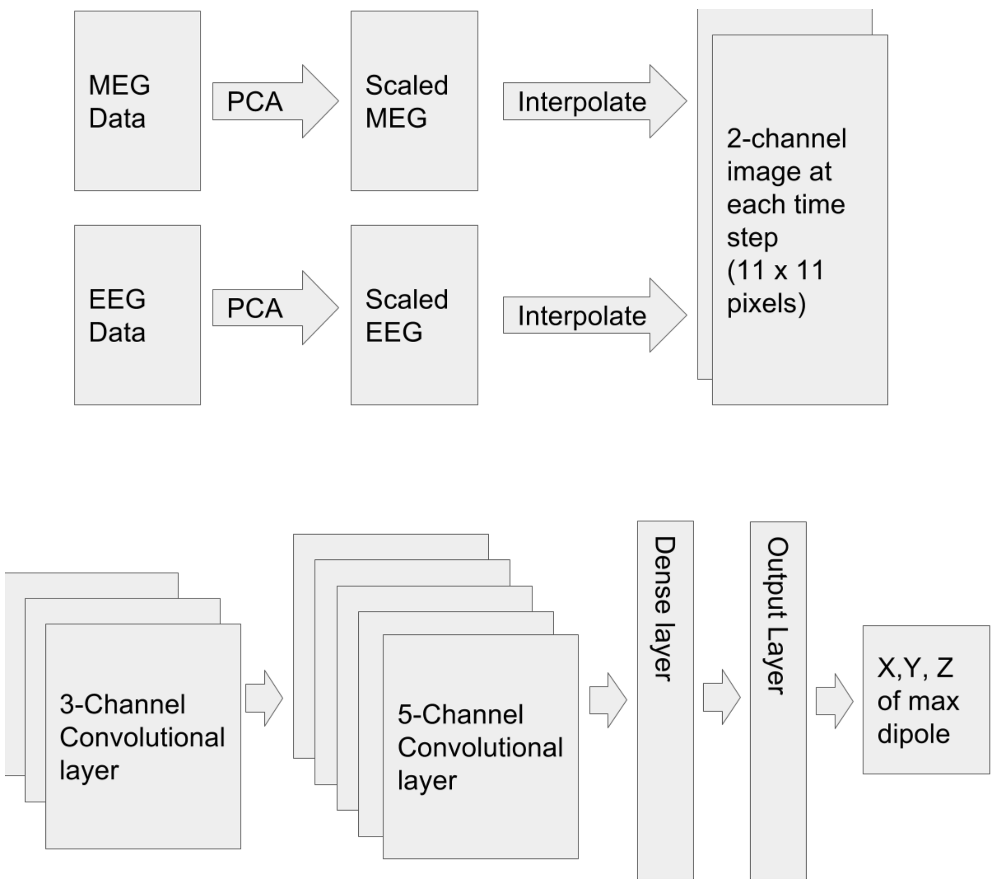

Fig. 2. Block diagram of CNN neural network.

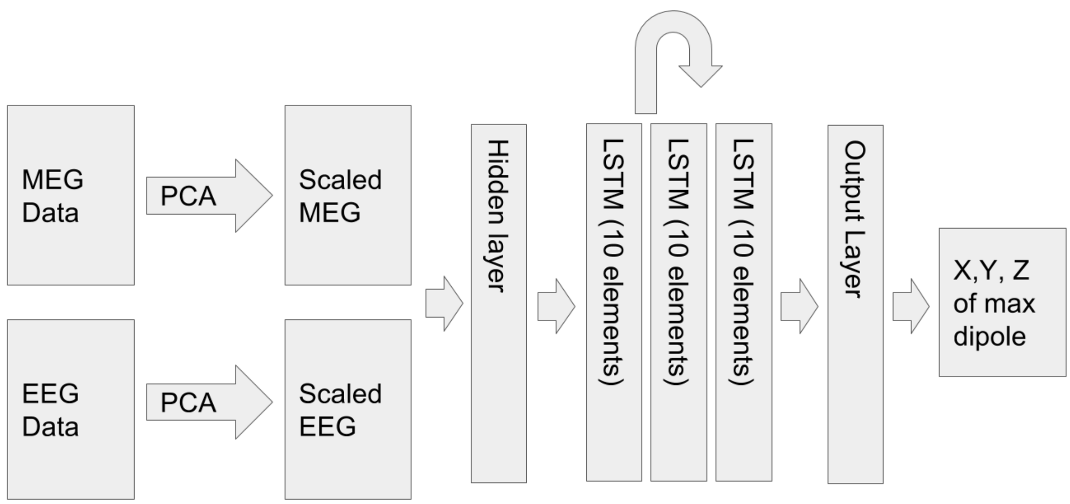

Fig. 3. Block diagram of RNN neural network.

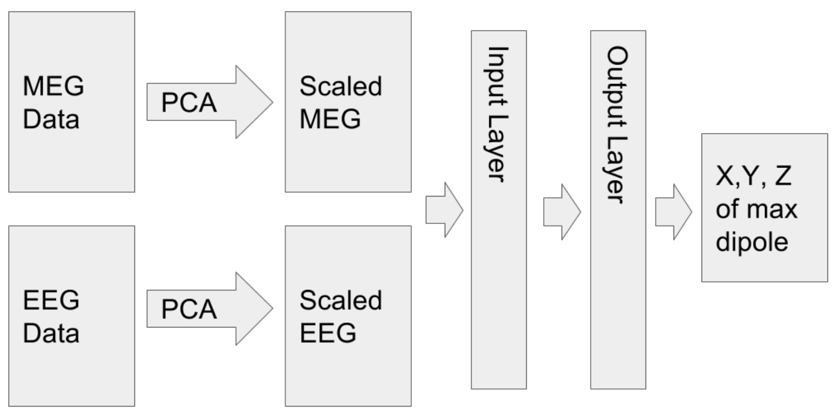

Fig. 4. Block diagram of MLP neural network.