

# EEG and MEG Inversion Using Convolutional and Recurrent Neural Networks

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**Abstract**—Real-time localization 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 architectures 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 structure 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 known 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 original 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. The signal-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 appropriately 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.

## II. METHODS

In this section, we describe our methodology, including datasets, preprocessing, and neural network architectures.

1) *Datasets*: To test our method, we used two multimodal datasets. Both were processed using the python-mne package [15].

One dataset [16] consisted of 19 subjects presented with stimulus of famous, unfamiliar, or scrambled faces. There

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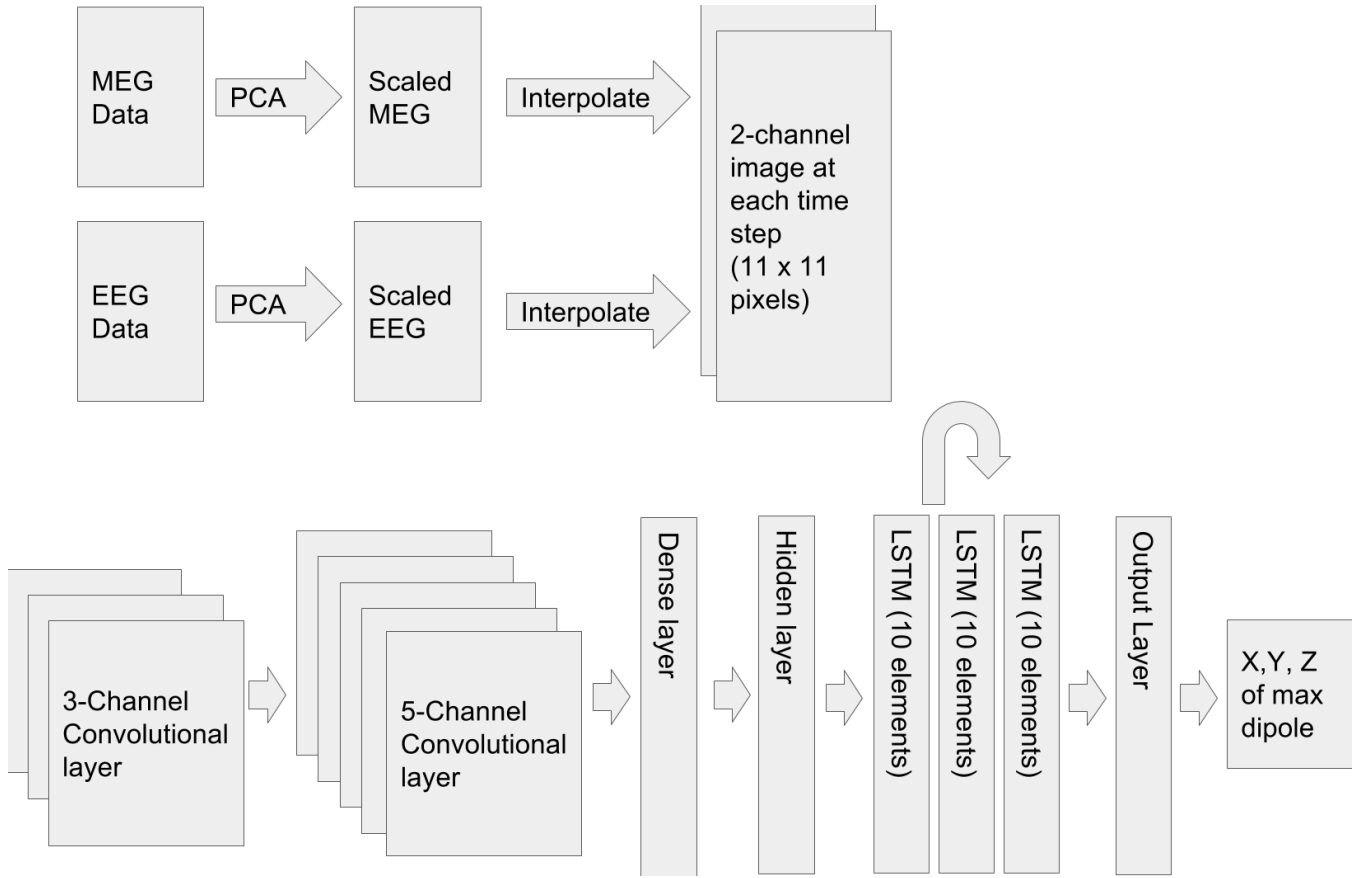


Fig. 1. Block diagram of CNN+RNN neural network.

were 102 magnetometers, 204 planar gradiometers, and 70 electrodes, with 3 electrodes used for ocular and cardiac artifacts. We excluded gradiometers, as our study is to develop an inversion technique for use with our own MEG system, which only has the radial magnetometers. We considered one subject only (sub007) as that subject's MRI was the only one to segment properly into skin, skull, and cortex layers (an important feature for the inversion step). We used the data processing pipeline provided with the dataset here: <http://mne-tools.github.io/mne-biomag-group-demo/>. Sampling rate 1100 Hz 551 time points per trial, ico-4

The second dataset [17] is included with MNE. ... one ocular channel 59 eeg 102 mag oct-5 checkerboard patterns were presented into the left and right visual field, interspersed by tones to the left or right ear.

#### A. Preprocessing

#### B. Description of Neural Networks

tensorflow.com [18]

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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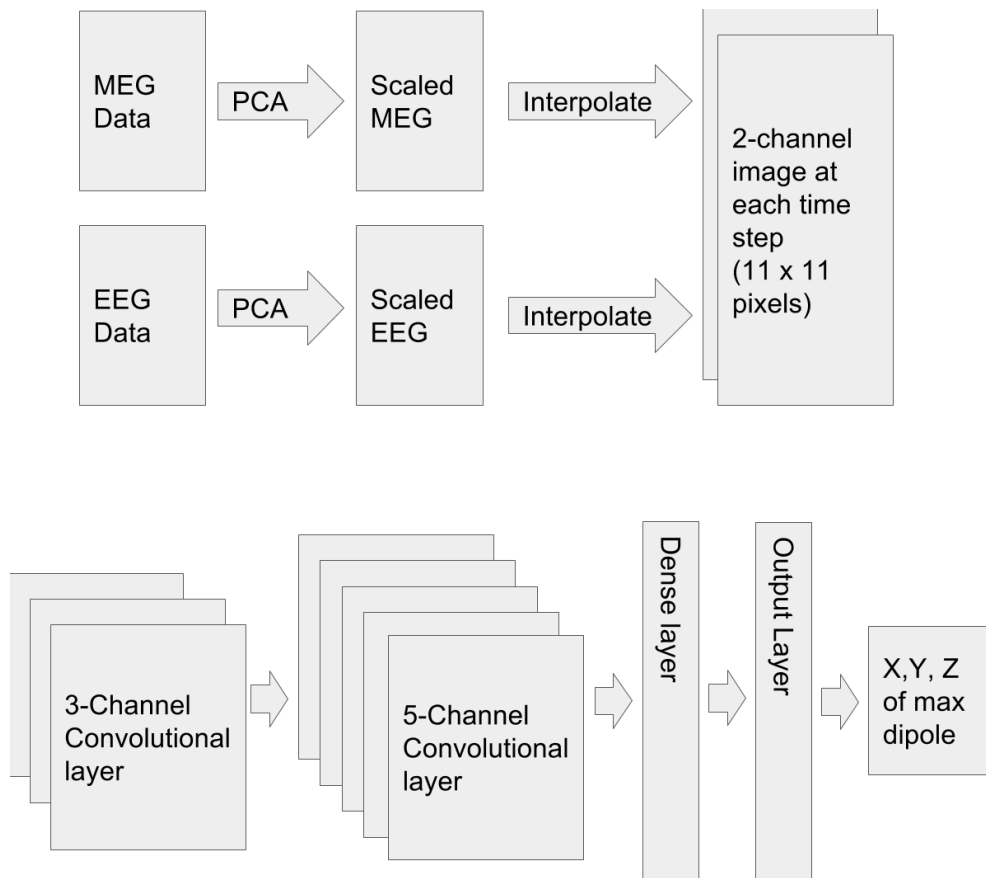


Fig. 2. Block diagram of CNN neural network.

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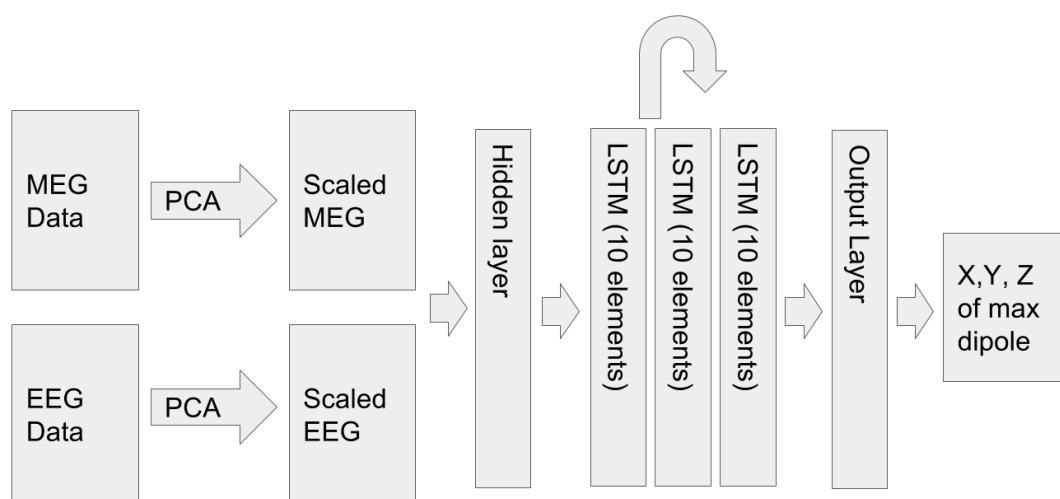


Fig. 3. Block diagram of RNN neural network.

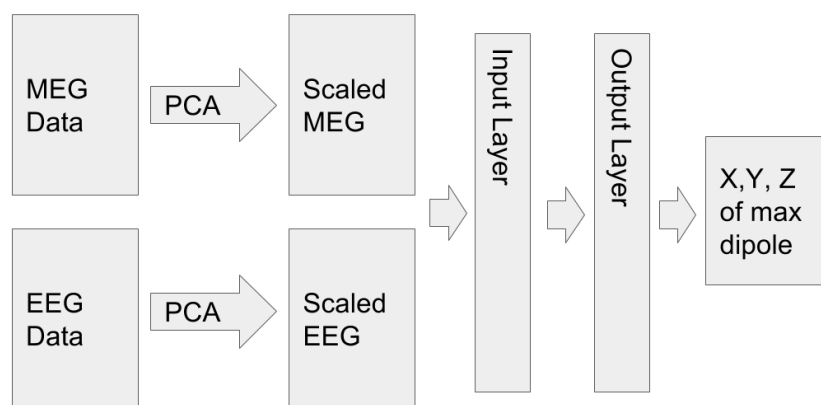


Fig. 4. Block diagram of MLP neural network.

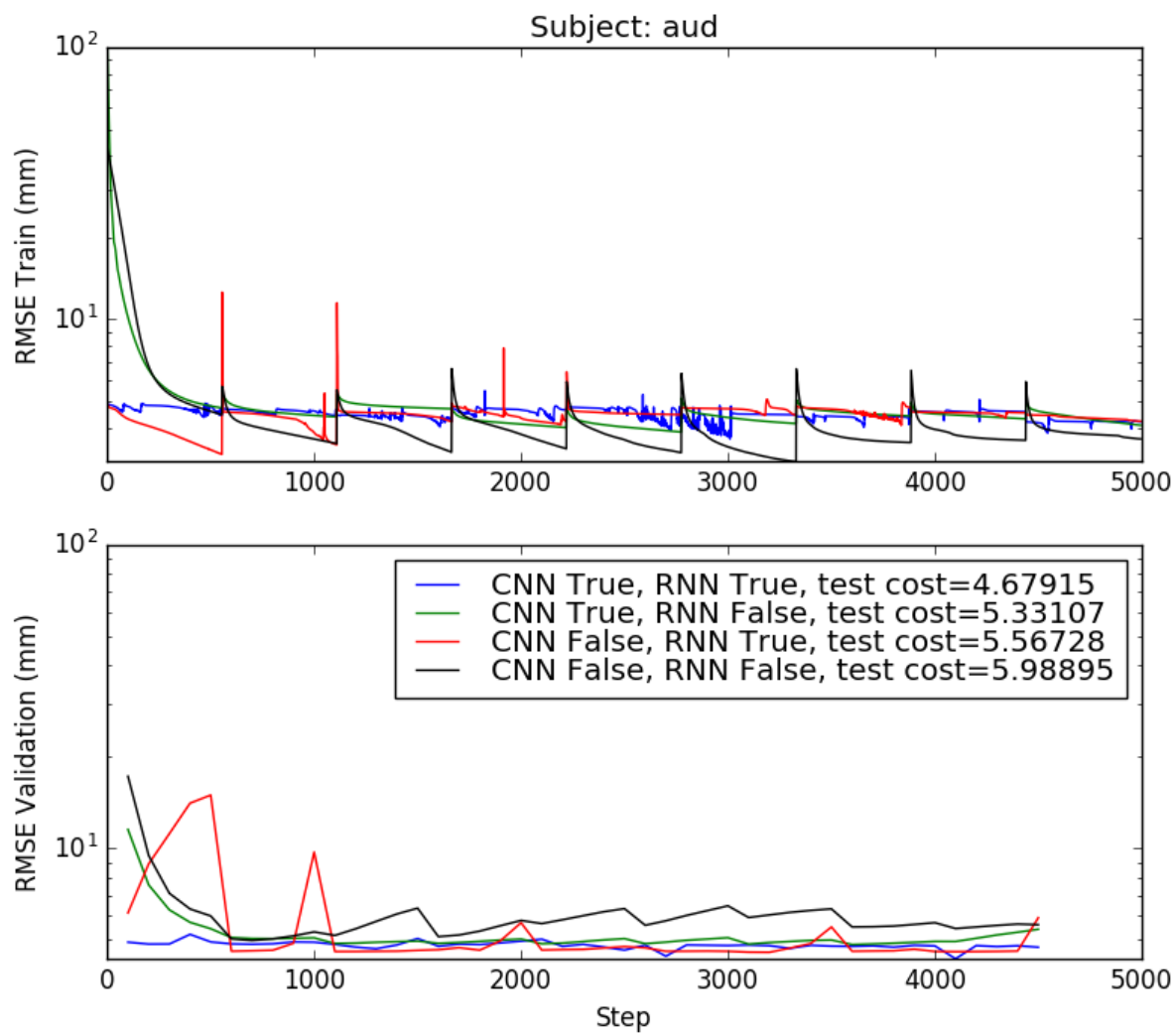


Fig. 5. Training/validation results for auditory stimulus dataset (1 dipole).

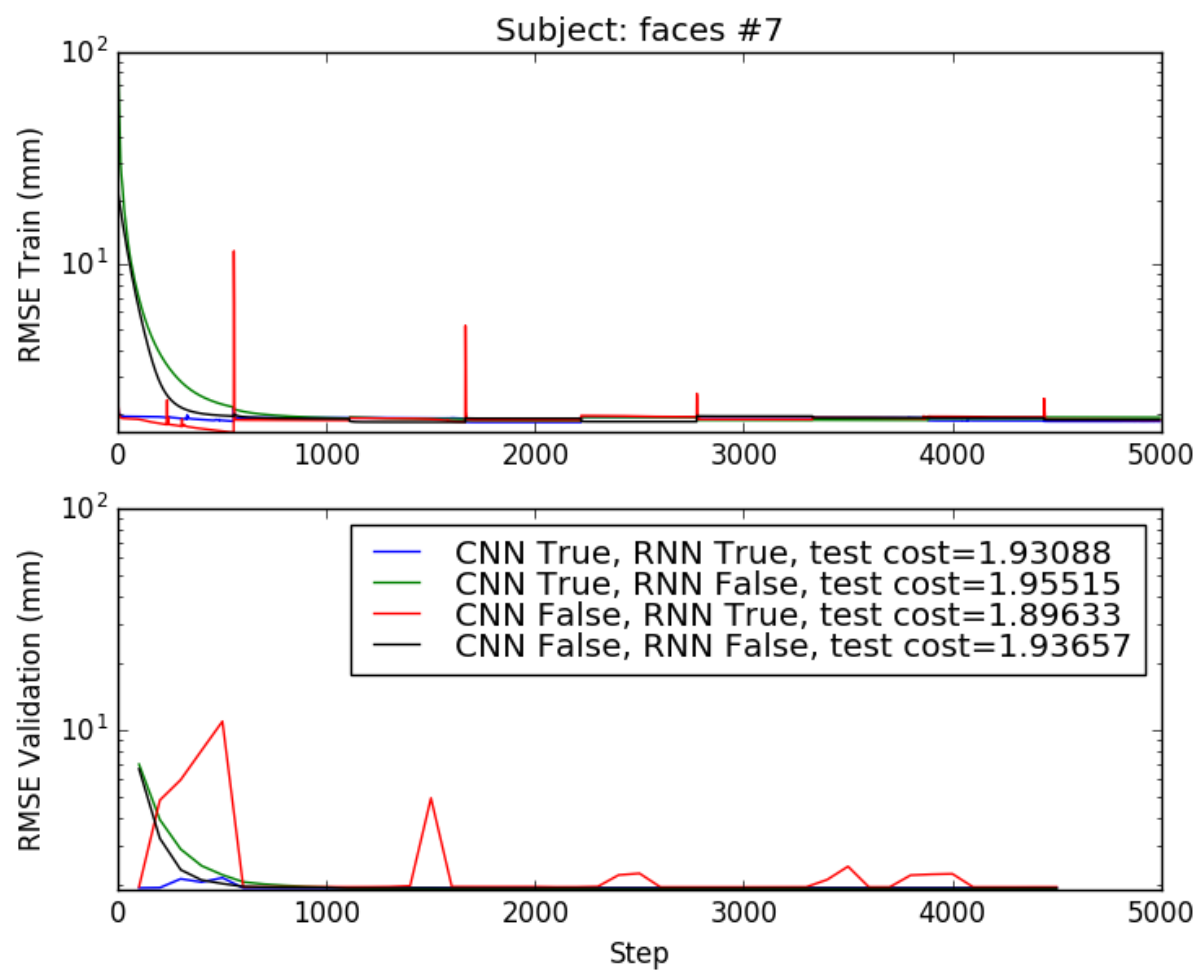


Fig. 6. Training/validation results for faces stimulus dataset (1 dipole).

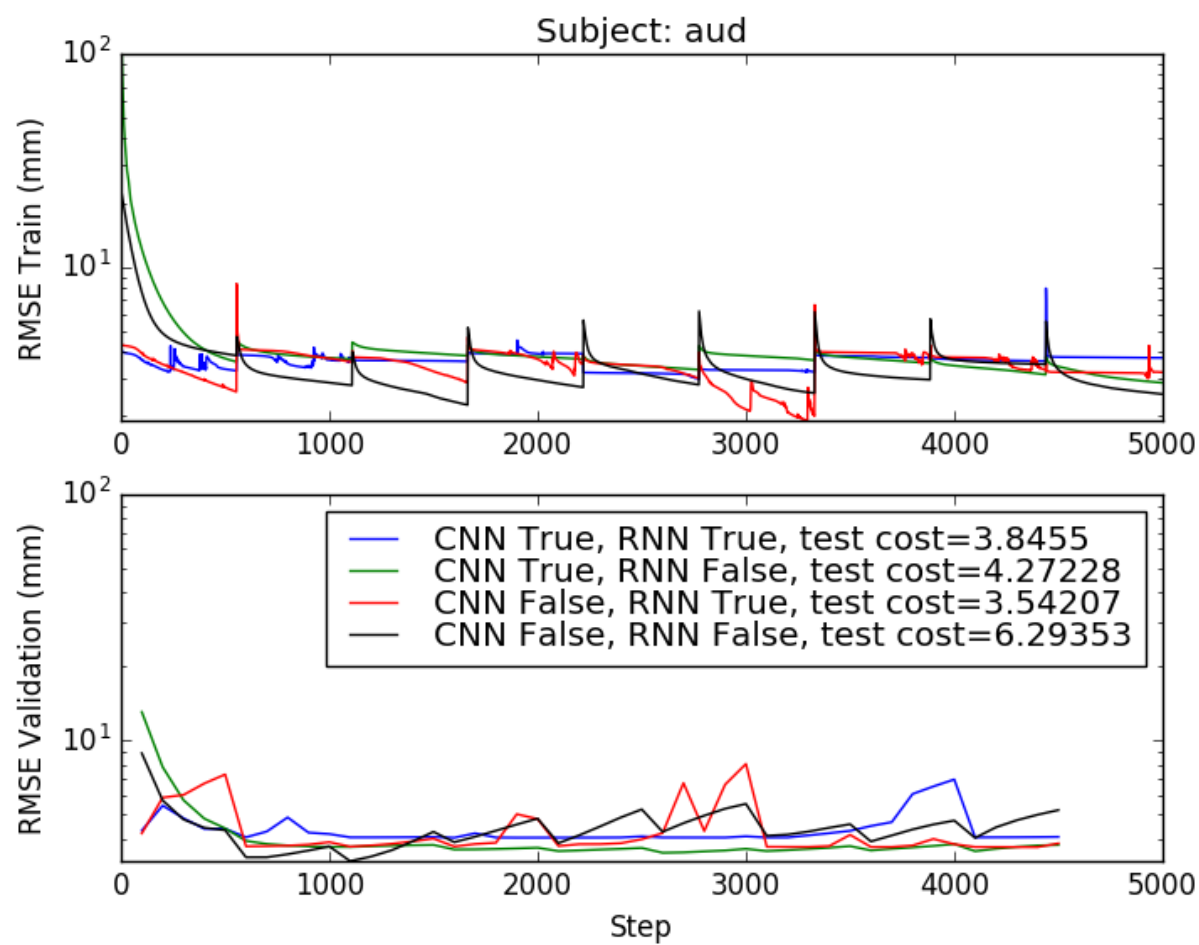


Fig. 7. Training/validation results for auditory stimulus dataset (best of 10 dipoles).



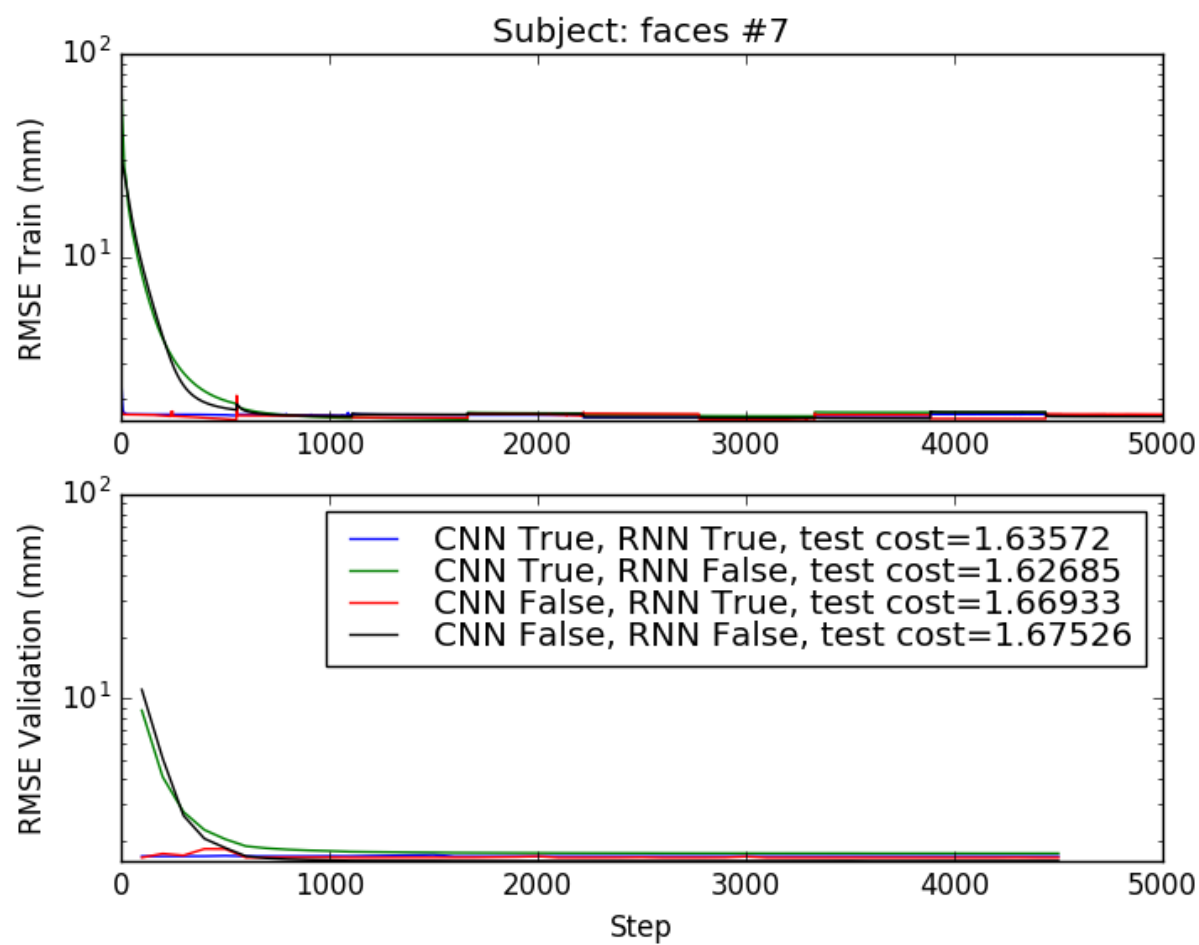


Fig. 8. Training/validation results for faces stimulus dataset (best of 10 dipoles).

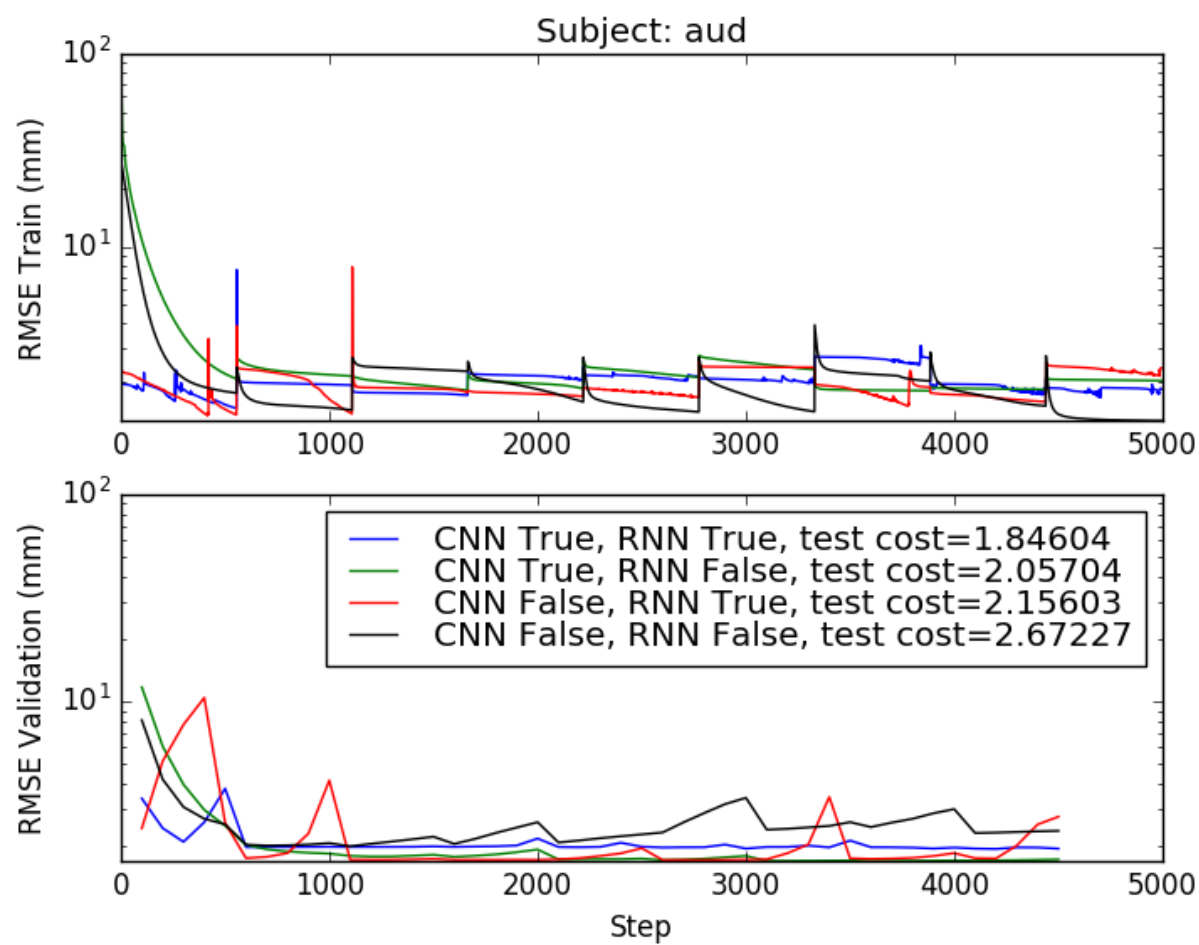


Fig. 9. Training/validation results for auditory stimulus dataset (best of 100 dipole).

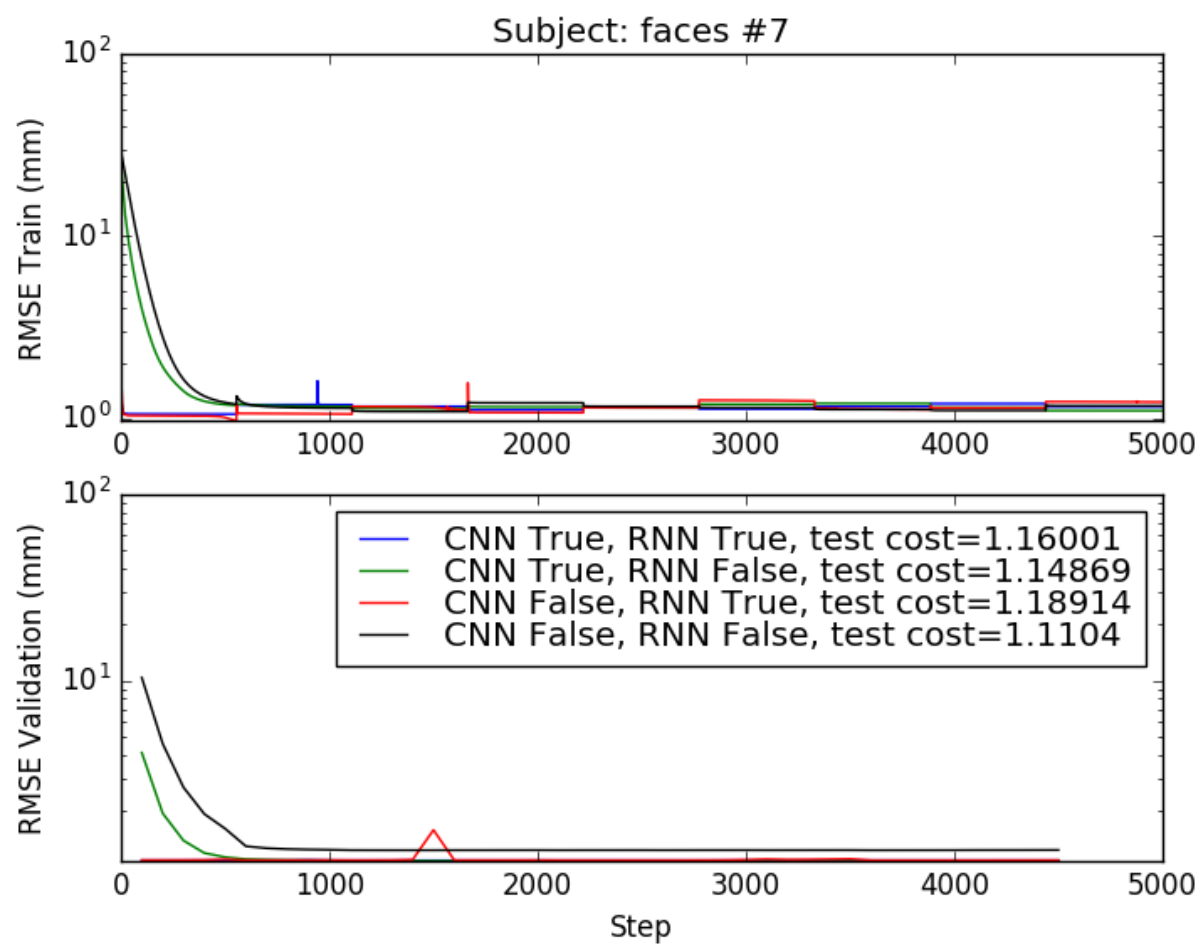


Fig. 10. Training/validation results for faces stimulus dataset (best of 100 dipoles).