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Master’s thesis

Localization and identification of Neural Sources from simulated EEG Signals

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Contents

Introduction

Electroencephalography (EEG) is a method for recording electric potentials stemming from neural activity at the surface of the human head, and it has important scientific and clinical applications. An important issue in EEG signal analysis is so-called source localization where the goal is to localize the source generators, that is, the neural populations that are generating specific EEG signal components. An important example is the localization of the seizure onset zone in EEG recordings from patients with epilepsy. A drawback of EEG signals is however that they tend to be difficult to link to the exact neural activity that is generating the signals.

Source localization from EEG signals has been extensively investigated during the last decades, and a large variety of different methods have been developed. Source localization is very technically challenging: because the number of EEG electrodes is far lower than the number of neural populations that can potentially be contributing to the EEG signal, the problem is mathematically under-constrained, and additional constraints on the number of neural populations and their locations must therefore be introduced to obtain a unique solution.

For the purpose of analyzing EEG signals, the neural sources are treated as equivalent current dipoles. This is because the electric potentials stemming from the neural activity of a population of neurons will tend to look like the potential from a current dipole when recorded at a sufficiently large distance, as in EEG recordings. Source localization is therefore typically considered completed when the location of the current dipoles has been obtained. However, an exciting possibility is to try to go one step further and identify the type of neural activity that caused a localized current dipole. For example, the type of synaptic input (excitatory or inhibitory) to a population of neurons, and the location of the synaptic input (apical or basal) will result in different current dipoles (Ness et al., 2022). It has also been speculated that dendritic calcium spikes can be detected from EEG signals, which could lead to exciting new possibilities for studying learning mechanisms in the human brain (Suzuki & Larkum, 2017). Identifying different types of neural activity from EEG signals would however require knowledge of how different types of neural activity are reflected in EEG signals. Tools for calculating EEG signals from biophysically detailed neural simulations have however recently been developed, and are available through the software LFPy 2.0 (Hagen et al., 2018; Næss et al., 2021). This allows for simulations of different types of neural activity and the resulting EEG signals, opening up for a more thorough investigation of the link between EEG signals and the underlying neural activity.

The past decade has seen a rapid increase in the availability and sophistication of machine learning techniques based on artificial neural networks, like Convolutional Neural Networks (CNNs). These methods have also been applied to EEG source localization with promising results. However, it has not been investigated if CNNs can also identify the neural origin of EEG signals, in addition to localizing neural sources. In this Master's thesis, the aim will be to investigate the possibility of using CNNs to not only localize current dipoles but also identify the neural origin of different types of neural activity, based on simulated data of different types of neural activity and the ensuing EEG signal.

0.1 Motivation

0.2 Goal and Objectives

0.3 Structure of the Thesis

Chapter 1

Background

Neurobiology is the study of the nervous system, including the structure, function, and development of neurons and neural circuits. The physics of the neuron is an important component of neurobiology, as it involves understanding the mechanisms by which neurons generate and transmit electrical signals. The basic unit of the nervous system is the neuron, which is capable of producing and transmitting electrical signals, or action potentials, across its membrane. These electrical signals are generated by the flow of charged ions into and out of the neuron, and are essential for communication between neurons and the transmission of information throughout the nervous system.

One technique for studying the electrical activity of the brain is electroencephalography (EEG), which measures the voltage fluctuations resulting from the electrical activity of neurons. EEG is a non-invasive technique that involves placing electrodes on the scalp, and has been used to study a wide range of cognitive and neural processes, including perception, attention, and memory. One of the challenges of interpreting EEG signals is the "inverse problem," which involves determining the location and nature of the underlying sources of electrical activity in the brain.

One approach to solving the inverse problem is source localization, which involves estimating the location and strength of the electrical sources in the brain that are responsible for the measured EEG signals. Source localization is a challenging problem due to the complexity of the brain and the fact that EEG signals are affected by a range of factors, including the conductivity of the scalp and the position and orientation of the electrodes. However, there are a number of techniques and algorithms that have been developed to address these challenges, including dipole modeling, distributed source modeling, and beamforming (Hämäläinen et al., 1993; Grech et al., 2008).

Overall, the physics of the neuron, EEG, and source localization are all important components of neurobiology that have contributed to our understanding of the nervous system and its functioning. By combining knowledge of the physical principles of neural signaling with advanced analytical techniques, researchers are able to gain valuable insights into the underlying neural processes that give rise to behavior and cognition.

1.1 Introduction to Neuroscience

1.2 Electroencephalograpy

1.3 The Inverse Problem

Chapter 2

Electroencephalograpy

Some words about what the background chapter will include.

2.1 Neuroscience and Electroencephalography

Electroencephalography (EEG) is a non-invasively technique for studying electrical potentials in the human brain. The technique was developed almost a century ago making it among the oldest methods for examining the brain's activity. Today, EEG remains one of the most important techniques being used to study electrical activity in the brain, with important applications in both neuroscientific and clinical research (Nunez and Srinivasan 2006, Lopes da Silva 2013, Biasiucci et al. 2019, Ilmoniemi and Sarvas 2019).

EEG signal is believed to originate from large numbers of synaptic inputs to populations of geometrically aligned pyramidal neurons (Nunez and Srinivasan 2006, Pesaran et al. 2018).

Electroencephalography (EEG) is one of the most important techniques for studying cognition and disease in the brain non invasively. EEG is a method used to measure brain waves. In practice, this involves electrodes consisting of small metal disks connected to the surface of the scalp. The electrodes detect electrical charges that result from activity of the brain cells. In cases where certain areas of the brain come out as more active than others, it might indicate abnormalities, in which can be signs of disease. In other words, the EEG technique can be used to evaluate multiple types of brain disorders, such as lesions of the brain, Alzheimer's disease, epilepsy or brain tumors.

An illustration of the typical EEG measurement setup is depicted in Figure 2.1.

EEG signals are generated from synaptic inputs to cells in the cortex. Synaptic inputs are electrical (or chemical) signals that are being transmitted from one neuron to another, causing changes in the membrane potential of the neurons. In other words, neurons are specialized to pass signals, and

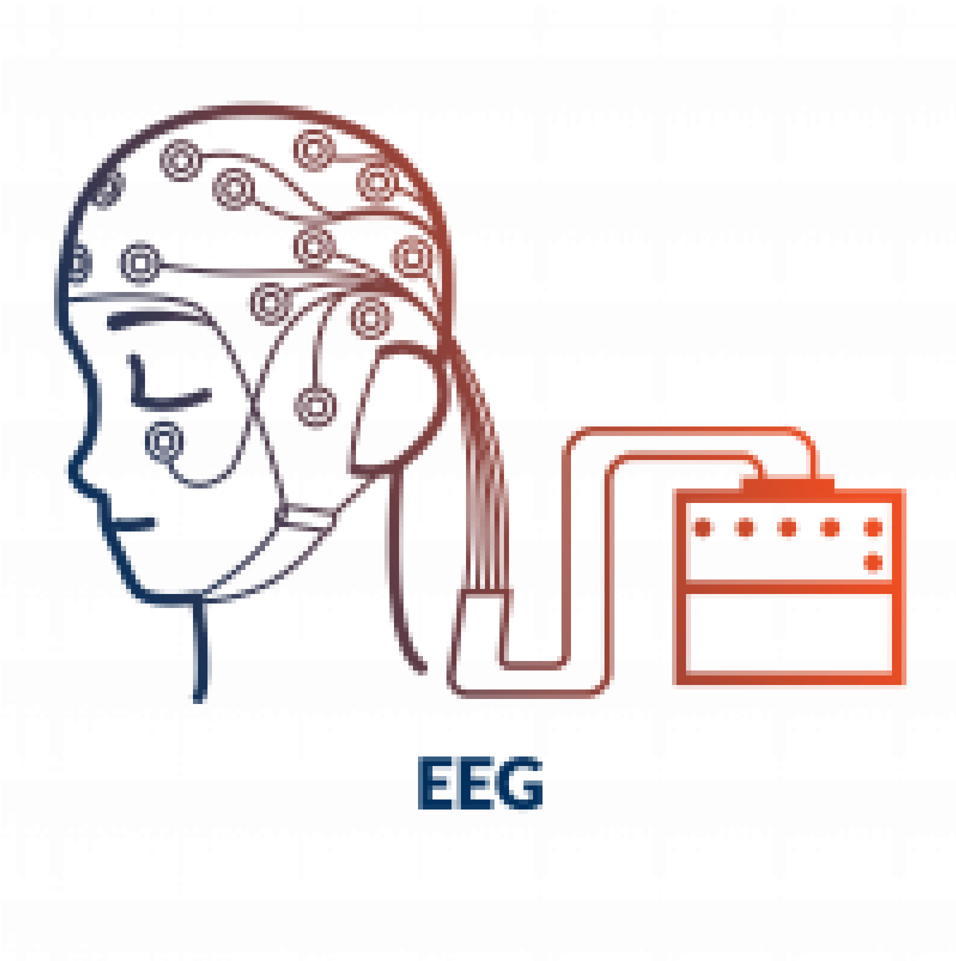

Figure 2.1: Illustration of the EEG method.

synapses are the structures that make this transmission possible.

Imagining a small part of the cortex, all of these cells will have dendrites pointing upwards in the same direction (lets say the z-direction). Due to rotational symmetry around the z-axis, the contributions in the x- and y-direction will cancel. This is illustrated in Figure 2.2. What we see is that the extracellular potential is configured in all sorts of weird ways (A-C) when there is only one synaptic input, while the extracellular potential reminds more of a dipole when we have multiple synaptic inputs (D-F). We can therefore argue that the total contribution to the extracellular potential can be modelled as a dipole in the z -direction for the case where we have multiple synaptic inputs. Hence, for each dipole moment in our simulations, we assume multiple synaptic inputs, and make sure to rotate the positions of the dipoles such that it is orientated along the depth of the cortex.

2.2 Currend Dipoles Approximation

EEG signals arise from cortical neural activity and are typically described in terms of current dipoles.

An optimal model of EEG signals would have consisted of multiple dipole moments. However, as such a model is complicated and computationally expensive, we will in this project only introduce one single dipole approximation $\mathbf{p}(t)$ for each multicompartmental neuron simulation. In this context, by multicompartmental modelling we refer to the widely used models within neuroscience, which acurately manufactures electical properties of single neurons. The sigle-dipole approximation might sound like a substantial simplification of the real biophysical properties, nevertheless it actually turns out to give a realistic modelling of EEG signals, when handling the single dipole moment, as an abnormality in the brain. We will be thinking of the abnormality as an epileptic seizures or a tumor in the brain, which among normal activity in the brain would have stuck out. The single-dipole approximation is implemented by summing up the multiple current dipole moments,

$$\mathbf{p}(t) = \sum_{k=1}^{M} \mathbf{p}_k(t) = \sum_{k=1}^{M} I_k^{axial}(t)\mathbf{d}_k, \tag{2.1}$$

where I^{axial} is the current flowing along the neurite with the distance vector $\mathbf{d}_k$ and M denotes the number of axial currents. The data set we will be using in this project will consist of measures of different EEG signals at a given time from 1000 patients. This means that we for each patient pick a random location (at $t = 0$) for the single current dipole.

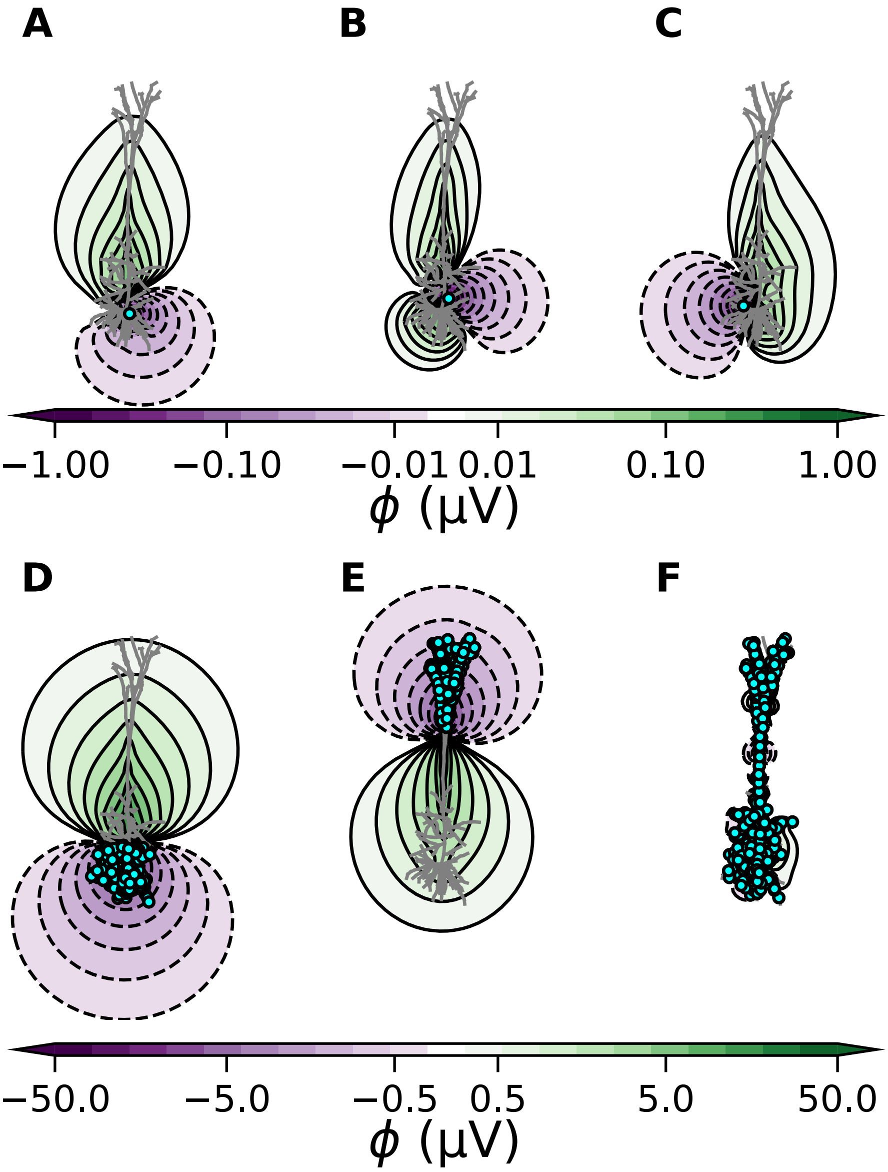

Figure 2.2: Extracellular potential from lonely synaptic input (A-C) and extracellular potential from multiple synaptic inputs (D-F).

2.3 The New York Head Model

The signals received from EEG are known to originate from cortical neural activity, which are often described by using current dipoles. It is therefor reasonable to implement current dipoles in the brain for when generating a biophysical modeling of EEG signals. The brain model used in this thesis is called the New York Head model, and is based on high-resolution anatomical MRI-data from 152 adult heads. The model utilizes the software tool LFPy, which is a Python module for calculation of extracellular potentials from multicompartment neuron models. This model takes into account that electrical potentials are effected by the geometries and conductivities of various parts of the head.

The cortex matrix consists of 74382 points, which refer to the number of possible positions of the dipole moment in the cortex. When generating our data set, we will for each sample randomly pick the position of the dipole moment, such that one sample corresponds to one patient. In our head model we are considering 231 electrodes uniformly distributed across the cortex, meaning that each EEG sample will consist of this many signals for each time step. However, we are not interested in the time evolution of the signals as this does not affect nor say anything about the position of the dipole moment, and we therefor simply pick out the EEG signals for when $t = 0$ (note that the choice of time step could have been randomly picked). Our final design matrix will then consist of 1000 rows, corresponding to each patient, and 231 columns also refereed to as features, representing the signal of each electrode. The final output we are trying to predict is then the one dimensional vector with length 1000, where each element consists of the x-, y- and z- position of the dipole moment. An example of how the input EEG signals may look like is given in appendix A, where we also have marked the dipole moment with a yellow star.

2.4 The Inverse Problem and Source Localization

Chapter 3

Methods

3.1 Head Models and Multicompartmental Modeling

3.2 Currents and Potentials in the Brain

Ohm's law in volume conductors is a more genral statement than its usual form in electrical circuits. It is a linear relationship between vector current density J and the electric field E. The law is then expessed as follows:

$$J = \sigma E, \tag{3.1}$$

where σ is the conductivity of the .... (physical material). (Soruce: Electric Fields of the Brain: The Neurophysics of EEG).

3.3 New York Head Model

Neurons communicate with each other through the use of electical currents. When a neuron receives a signal, it generates an electrical current that propegates along the axon and causes the release of neurotransmitters that diffuse across the gap between the sending and the recieving neuron. If the neurotransmitters are accepted by the receptors on the recieving neuron, a new electrical signal will be generated. This process of electrical communaication between neurons creates electromagnetic fields that can be measured using electroencephalography (EEG).

A central problem for EEG is to relate scalp data to brain *current sources* (Electric Fields of the Brain: The Neurophysics of EEG)....

Especially important for electrode locations outside of the brain, such as EEG, is the knowledge about how the electrical potentials will be affected by the geometries and conductivites of the various parts of the head (Biophysically detailed forward modeling of the neural origin of EEG and MEG signals).

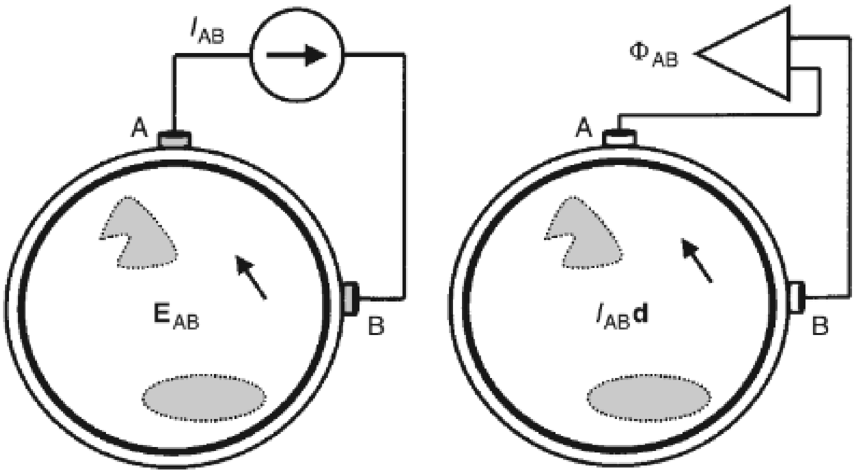

Figure 3.1: A caption here is needed.

A model that takes these detailes into account is the New York Head Model. The model is based on anatomical and electrical characteristics of 152 adult human brains and is solved for 231 electrode locations.

The New York Head Model is a computer model of the human head used to simulate the electrical activity of the brain. It was created by the Electrical Geodesics Incorporated (EGI) in 2004, and is based on the anatomical and electrical characteristics of the head of a typical adult human. The model consists of a three-dimensional (3D) representation of the head and brain, with detailed information on the geometry and electrical properties of the different tissues and structures within the head. The model includes the scalp, skull, cerebrospinal fluid, gray matter, and white matter. The electrical properties of each of these tissues, such as conductivity and permittivity, are also included in the model.

The model was developed to be used for, and improve the accuracy of EEG source localization (The New York Head—A precise standardized volume conductor model for EEG source localization and tES targeting). To generate predictions of the EEG signals recorded from different scalp locations in response to a given set of source currents, the New York head model uses the lead field matrix (SOURCE), which is a mathematical representation of the relationship between the electrical activity in the brain and the electrical potentials recorded on the scalp.

The lead field matrix is constructed by taking advantage of the reciprocity theorem that states that knowledge of the current density through a volume conducter caused by an injection of current between two stimulating electrodes completely specifies how those same recording electrodes pick up potentials caused by dipole sources in the volume conducter. If one suppose that a pair of stimulating electrodes is placed at locations A and B on the scalp as provided in figure 3.1, an external current source will cause current to flow from electrode B through the brain, and all the way to electrode A. However, due to the geometry, inhomogeneity, and ansisotropy of the head, the current density will vary with location. The amount of current that pass through the brain depends, to a great extent, on the location of the electordes. In general, the brain currents will decrease with decreasing distance between electrodes. Thus, for a fixed pair of electrodes, the lead field vectors can be calculated as a function of position throughout the volume conducter. At each location, the orientation of the lead field vector L_{AB} is the orientation of the dipole source that produces the largest potential difference between the electrodes. The lead field matrix, L is given as:

$$L = \frac{E}{I}, \tag{3.2}$$

where I is the injected current at the electode locations and E is the resulting electric field in the brain (Biophysically detailed forward modeling of the neural origin of EEG and MEG signals). Moreover, the precise link between a current dipole moment p in the brain and the resulting EEG signals Φ is then related to the lead field matrix as follows:

$$\Phi_{AB} = L_{AB} \cdot p, \tag{3.3}$$

Here, an injected current I of 1 mA gives an electric potential E in V/m, meaning that a current dipole moment $\mathbf{p}$ in the unit of mAm gives EEG signals in the unit of V.

The New York Head model has been incorporated in the Python module LFPy, which provides classes for calculation of extracellular potentials from multicomparment neuron models. Read more: https://lfpy.readthedocs.io/en/latest/readme.htmlsummary

3.4 Machine Learning and Neural Networks

The feedforward neural network (FFNN) was one of the first artificial neural network to be adopted and is yet today an important algorithm used in machine learning. The feed forward neural network is the simplest form of neural network, as information is only processed forward, from the input nodes, through the hidden nodes and to the output nodes.

Computational neuroscience is a field that aims to understand the principles underlying information processing in the brain using mathematical and computational tools. The inverse problem in EEG, which involves estimating the location and strength of electrical sources in the brain based on measurements of electrical activity on the scalp, is a key challenge in computational neuroscience. Machine learning techniques, including feedforward neural networks, have been used to address this problem by learning to map the measured EEG signals to estimates of the underlying electrical sources in the brain.

Source localization using machine learning techniques has shown promise for improving the accuracy and efficiency of EEG analysis, and has been applied to a variety of cognitive and clinical applications. For example, machine learning-based source localization has been used to study the neural mechanisms underlying attention, memory, and perception (Wu et al., 2018; Lopes da Silva et al., 2019), as well as to diagnose and monitor neurological disorders such as epilepsy (Safieddine et al., 2019; Shah et al., 2020). These applications demonstrate the potential of machine learning and computational neuroscience to enhance our understanding of the brain and improve clinical outcomes.

Machine learning is a field of computer science that involves using algorithms and statistical models to enable computers to learn from data without being explicitly programmed. One popular type of machine learning algorithm is the feedforward neural network, which is a type of artificial neural network that is often used for tasks such as linear regression. In a feedforward neural network, data is passed through a series of layers of interconnected nodes, or "neurons," which perform mathematical operations to transform the data.

Linear regression is a common machine learning task that involves predicting a continuous quantity, such as the price of a house or the temperature of a city, based on a set of input features. In a feedforward neural network, linear regression can be accomplished by using a single neuron in the output layer of the network that computes a weighted sum of the input features and applies an activation function to produce the predicted output value. The weights on the input features are learned by the network during the training process, which involves adjusting the weights to minimize the difference between the predicted output values and the actual output values in the training data.

Overall, feedforward neural networks are a powerful machine learning tool that can be used to solve a wide range of problems, including linear regression. By adjusting the weights and biases of the neurons in the network during the training process, neural networks can learn to make accurate predictions based on input data, making them a valuable tool for a variety of applications.

Chapter 4

Dipole Source Localization using Neural Networks

In this chapther we will be presenting the neural networks used for the localization of current dipole sources in the human cortex.

4.0.1 Neural Networks

Artificial Neural Networks are computational systems that can learn to perform tasks by considering examples, generally without being programmed with any task-specific rules [1].

The biological neural networks of animal brains, wherein neurons interact by sending signals in the form of mathematical functions between layers, has inspired a simple model for an artificial neuron:

$$a = f\left(\Sigma_{i=1}^{n} w_i x_i + b_i\right) = f(z) \tag{4.1}$$

where the output a of the neuron is the value of its activation function f, which as input has the sum of signals $x_i, x_{i+1}, ..., x_n$ received by n other neurons, multiplied with the weights $w_i, w_{i+1}, ..., w_n$ and added with biases.

Most artificial neural networks consists of an input layer, an output layer and layers in between, called hidden layers. The layers consists of an arbitrary number of neurons, also referred to as nodes. The connection between two nodes is associated with a weight variable w, that weights the importance of various inputs. A more convenient notation for the activation function is:

$$a_i(x) = f_i(z^{(i)}) = f_i(w^i \cdot x + b^i) \tag{4.2}$$

where $w^{(i)} = (w_1^{(i)}, w_2^{(i)}, ..., w_n^{(i)})$ and $b^{(i)}$ are the neuron-specific weights and biases respectively. The bias is normally needed in case of zero activation weights or inputs [1].

4.1 Feed-Forward Neural Network Approach for localizing single dipole sources

The feedforward neural network (FFNN) was one of the first artificial neural network to be adopted and is yet today an important algorithm used in machine learning. The feed forward neural network is the simplest form of neural network, as information is only processed forward, from the input nodes, through the hidden nodes and to the output nodes.

4.1.1 DiLoc

The FFNN that are trained to solve the inverse problem of ours has an input layer of 231 neurons, corresponding to the M = 231 electrode measures of the potentials. The input layer is followed by three hidden layers with 120, 84 and 16 hidden neurons, respectively. When the aim is to estimate the localization of the current dipole, *only*, the final output layer holds the predicted x-, y- and z- position of the desired dipole source. However, if the interest lies in determining the size of the dipole population, an alternative output layer is incorporated in the network architecture providing the radius of the dipole(s), in addition to the location coordinates. This enables the model to provide a more comprehensive understanding of the dipole source(s) being analyzed.

4.1.2 Activation functions, Batchsize and Optimization

For the neurons of the input layers we use the linear activation function ReLu, while for the neurons of the hidden and output layers, we chose the much used hyperbolic tangent activation function.

Cost function In order to train the network faster, one commonly split the data set into mini-batches, which is also done here. When splitting the data such a way, the weights of connection between neurons are updated after each propagation, making the network converge considerable faster.

Scaling Every potential distribution presented to the network is first average referenced by subtracting the average of all potential values. Subsequently, the average referenced potentials are normalized by dividing them by the magnitude of the largest. The dipole location parameters are normalized to 1 with respect to the radius of the outer head boundary in the spherical head model (9.2 cm). In the case of a realistically shaped head model, the location parameters are normalized with respect to the radius of the best-fitting sphere for the scalp–air interface.

As was pointed out in the previous section, the optimal dipole orientation (in the leastsquares sense) for a given location can be calculated in a straightforward manner. Therefore, we will use neural networks to estimate only the dipole location parameters.

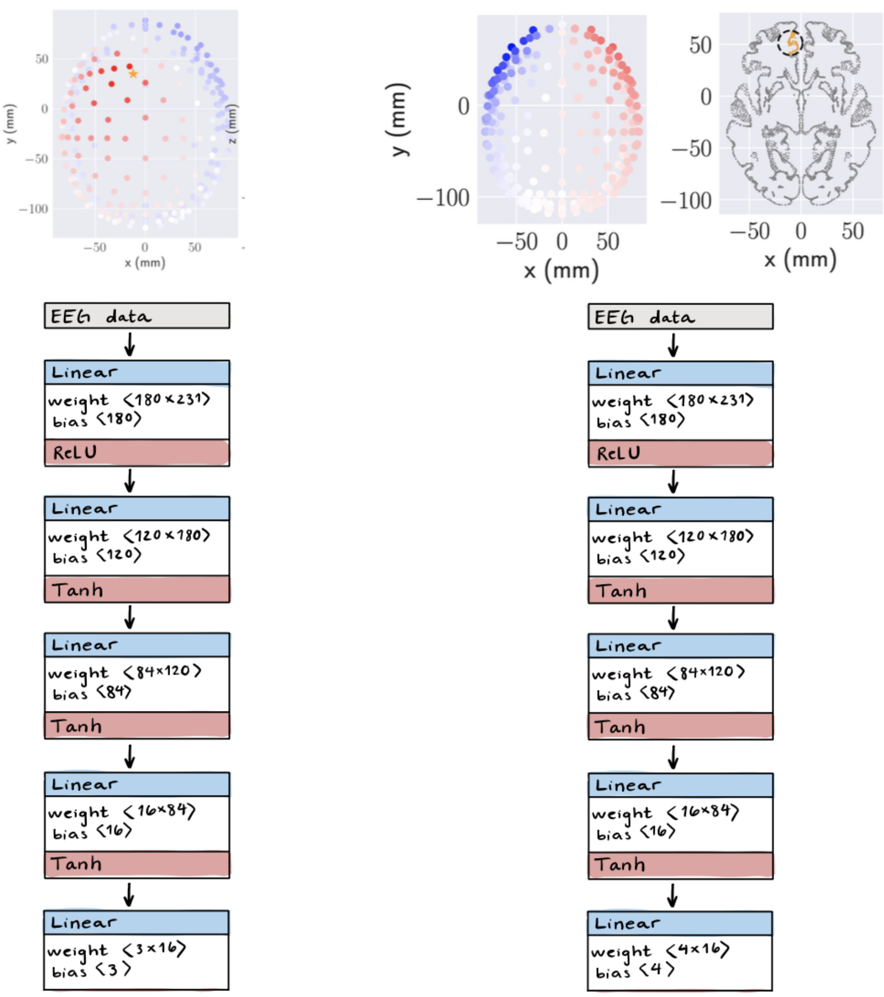

Figure 4.1: A caption here is needed.

4.1.3 Training, testing and evaluation

In order to make an ANN that generalizes well to new data we split our data into training and testing sets. Randomly selecting 80 percent of the rows in the full dataset, we put this into a separate one and call it our training set. The remaining 20 percent is put into the test set. In practice, the training data set consists of pairs of an input vector with EEG signals and the corresponding output vector, where the answer key is the x-, y- and z coordinate of the dipole source. The neural network is then feed with the training data and produces an estimation of the localization of the dipole. The estimation is found by the network through optimizing the parameters β minimizing the cost function, or said in other words, through finding parameters for the function that produces the smallest outcomes, meaning the smallest errors. The result provided by the network is then compared with the target, for each input vector in the training data. Adjustment of parameters...

When the network is fully trained, we have a final model fit on the training data set. Feeding the network with the test data set, we can assess the performance of the network. The predictions of the fully trained network can now be compared to the holdout data's true values to determine the model's accuracy.

In figure **??** we have provided the bias-variance trade-off for when using Tanh as activation function. We notice that error of the model is approaching 0 and that the variance between the two curves decreases for an increasing number of epochs.

Bibliography

[1] Jensen, M, H., 2021, Constructing a Neural Network code, Tensor flow and start Convolutional Neural Networks

Chapter 5

Results

As mentioned in chapter 1, an important topic in EEG signal analysis is the inverse problem of going from measured EEG signals to localized equivalent current dipoles, so-called source localization. In this chapter we will present the training and performance of the neural networks presented in chapter 4. Section ... and ... deal with training of the simple feed forward neural network and presenting its results, while section ... will discuss how a convolution neural network can be used to obtain the same results. But first, we will take a look at the dataset being feed to the different networks.

5.1 Simulation of EEG Signals

The cortex matrix of the New York Head Model (NYHM) consists of 74382 points, which refer to the number of possible positions for localization of dipole sources. We will train the neural networks using a dataset of self-simulated EEG measurements that correspond to the electromagnetic fields generated by dipole sources. These sources will have randomly selected positions within the cortex matrix. However, to simplify the problem, the stengths of single dipoles (amplitude) are set to 10^7 nA μ m. Moreover, in the cases of single dipole source localization, the direction of the dipole moment is always rotated so that it is normal to the cerebral cortex. In some cases this will result in a dipole moment pointing perpendicular to the skull (directed towards an EEG electorde), while in other cases, due to the structure of the cortex, the dipole moment will point back into the cortex (but eventually towards an EEG electorde). The reason for this is that the human cortex is strongly folded, and the contribution to the EEG signal from a neural population (dipole moment) will depend on whether a dipole is located in a sulcus or a gyrus (source: BookTVN).

5.1.1 Effect of dipole location and orientation on EEG signals

As shown by/ discussed in .... (source: BookTVN) EEG signals are relatively insensitive to small changes in the *location* of neural current dipoles. Even though the intuitive thought might be that neurons in the upper cortical layers dominate the EEG due to the closer distance to the EEG electrode compared to neurons in the lower cortical layers, such differences in location acutually does not make conciderable differences. This finding can be explained by fact that the low conductivity of the skull generates a certain spatial low-pass filtering, that .... .

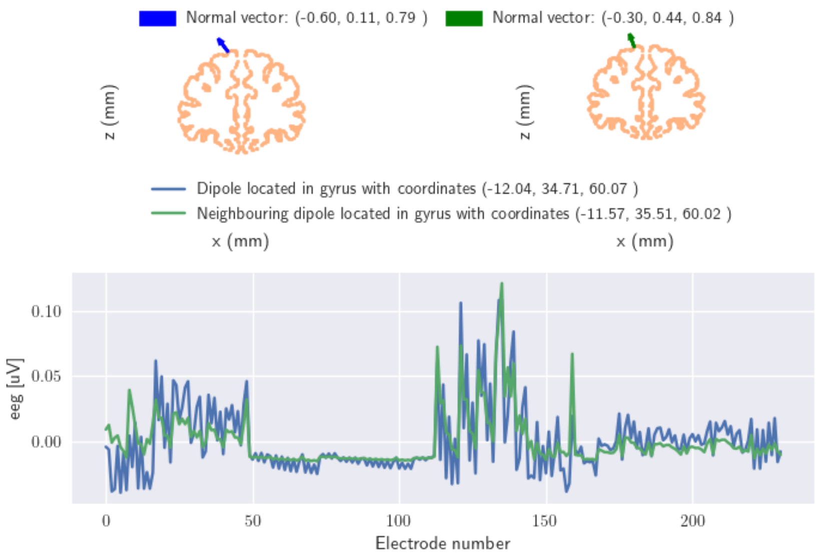

Figure 5.1: EEG signal for neighbouring dipoles.

However, in order to decribe the effect of the *orientation* of the dipoles relative to the EEG electrodes, we have in Figure 5.2 provided the EEG signals from two manually chosen dipole locations in the New York head model. The two dipoles illusrated are located in a gyrus and in a sulcus, both providing a different EEG outcome. In general, the EEG signal contribution from a single current dipole is maximized if the dipole is located in a gyrus, perpendicular oriented. Such a case is depiced in Figure 5.2B. However, if we place a dipole in a sulcus, again with perpendicular orientation, we can observe a substantial EEG contribution, but in contrast to the dipole in the gyrus we notice a more dipolar pattern 5.2C.

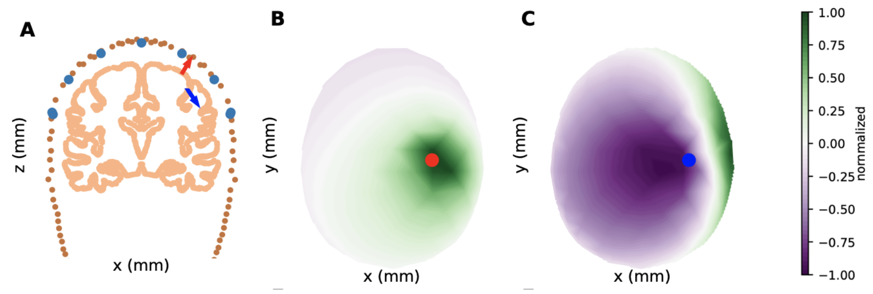

Figure 5.2: A: Two manually chosen dipole locations in the New York head model, located in a gyrus (red) and a sulcus (blue). The head model is seen from the side (x, z-plane). EEG electrode locations close to the chosen cross section plane are marked in light blue. The available dipole locations close to the cortical cross section effectively draw an outline of the cortical sheet, and are marked in pink. The current dipole moment was in all cases 10^7 nAμm. B: Interpolated color plot of EEG signal from the dipole in gyrus, seen from the top (x, y-plane). The plotted EEG signal is normalized but the maximal value was 1.1 μV. C: Interpolated color plot of EEG signal from the dipole in sulcus. The plotted EEG signal is normalized but the maximal value was 0.7 μV. (source: BookTVN)

5.1.2 Noise

As for all experimental data, real EEG recordings contain noise. Artifacts are signals recorded by EEG but with a origin different from those generated by human brain activity. As some artifact may mimic true epileptiform abnormalities or seizures, awereness of artifacts and methods for distinguishing such signals from brain waves is highly important (https://link.springer.com/chapter/10.1007/978-3-030-03511-2_8).

There are two different dypes of artifacts, classified according to their origin. Physiological artifacts originate from the patient itself, where the most usual ones are ocular activity, muscle activity, cardiac activity, perspiration and respiration. Technical artifacts, on the other hand, is generated from the environment of the patient, such as cable and body movements or electromagnetic interferences. (https://www.bitbrain.com/blog/eeg-artifacts).

Filtering techniques are usually utilized in order to remove artifact from EEG before analyzation of the recordings. But, when it comes to the simulated EEG data of ours, we are in no need to remove such noise, as there simply is none. The simulated EEG data can be understood as already filtered data that has undergone preprocessing steps, to ensure a high signal-to-noise ratio (https://en.wikipedia.org/wiki/Signal-to-noise-ratio). Moreover we understand the simulated data as an averaged measure of the typical EEG time series. However, in order to avoid overfiting and for other tecnical detailes, we do need to ass noise to tha data before feeding it to the neural network. Therefore, to the final dataset of ours we add normally distributed noise of 10 %, with mean .... and standard deviation ... .

5.2 Localizing Single Dipole Sources

5.2.1 The dataset

The data set used to train a simple feed forward neural network consists of 10 000 rows, where each row corresponds to one sample, or let us say - one patient. Within the data set we have 231 columns, also referred to as features, representing the EEG measure at every recording electrode. Thus, we are left with a design matrix of size 10 000 x 231.

An example of how the input EEG data may look like for one sample (before adding noise) is provided in figure 5.3. The figure illustrates the EEG result from a sample containing a single current dipole source at a random position within the celebral cortex. As also can be seen from the characteristic dipolar pattern, the dipole is located in a sulcus. The EEG measure is seen from both sides (x-, z-plane and y-, z-plane) and above (the x-, y-plane). EEG electrode locations are presented as filled circels, where the color of the fill represents the amplitude of the measured signal for the given electrode. The position of the current dipole moment is marked with a yellow star. As can be read off from the figure, the EEG signals, for this given sample, range from between -1 to 1 μV.

5.2.2 Validation accuracy

In Figure 5.4 we have provided the validation accuray, using mean squared error (MSE) and the coefficient of determination (R2-score).

The expression for MSE when predicting the x-, y- and z-coordinate, goes as follows:

$$MSE(\hat{y}, \tilde{\hat{y}}) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 = \frac{1}{3}\sum_{i=1}^{3}((x-\tilde{x})^2 + (y-\tilde{y})^2 + (z-\tilde{z})^2) \tag{5.1}$$

The coefficient of determination is given as follows:

$$R^2(\hat{y}, \tilde{\hat{y}}) = 1 - \frac{\sum_{i=0}^{n-1}(y_i - \tilde{y}_i)^2}{\sum_{i=0}^{n-1}(y_i - \bar{y})^2}, \tag{5.2}$$

Where the mean value of y_i is defined by $\bar{y}$:
$\bar{y} = \frac{1}{n}\sum_{i=0}^{n-1} y_i$.

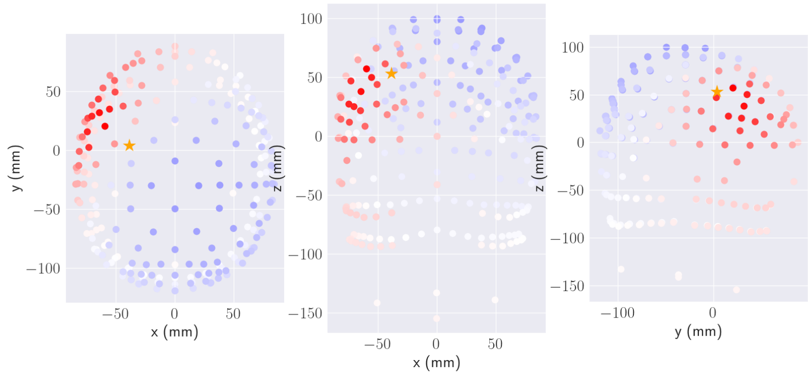

Figure 5.3: EEG for a sample containing one single current dipole source at a random position within the celebral cortex. The EEG measure is seen from both sides (x-, z-plane and y-, z-plane) and above (the x-, y-plane). EEG electrode locations are presented as filled circels, where the color of the fill represents the amplitude of the measured signal for the given electrode. The position of the current dipole moment is marked with a yellow star.

5.3 Convolution Neural Network Approach for localizing single dipole sources

Some results for the prediction of location for single current dipoles.

5.4 Region of Active Correlated Current Dipoles

Some results for the prediction of the size and location of current dipole populations.

Printed in terminal:

Epoch 9898/9999 | Train: 0.187 | Test: 4.275

Epoch 9899/9999 | Train: 0.184 | Test: 4.288

Epoch 9900/9999 | Train: 0.201 | Test: 4.279

Target: tensor([-1.0800, -1.9594, 0.4290, 11.0140])

Predicted: tensor([-1.1171, -1.9642, 0.4575, 16.5920])

Target: tensor([-6.7642e-02, 1.5426e+00, -1.0356e-02, 1.5576e+01])

Predicted: tensor([-0.3908, 1.4285, -0.1167, 15.9222])

Target: tensor([-0.6671, -1.0569, 1.8694, 7.1385])

Predicted: tensor([-0.7248, -1.0950, 1.9903, 6.2405])

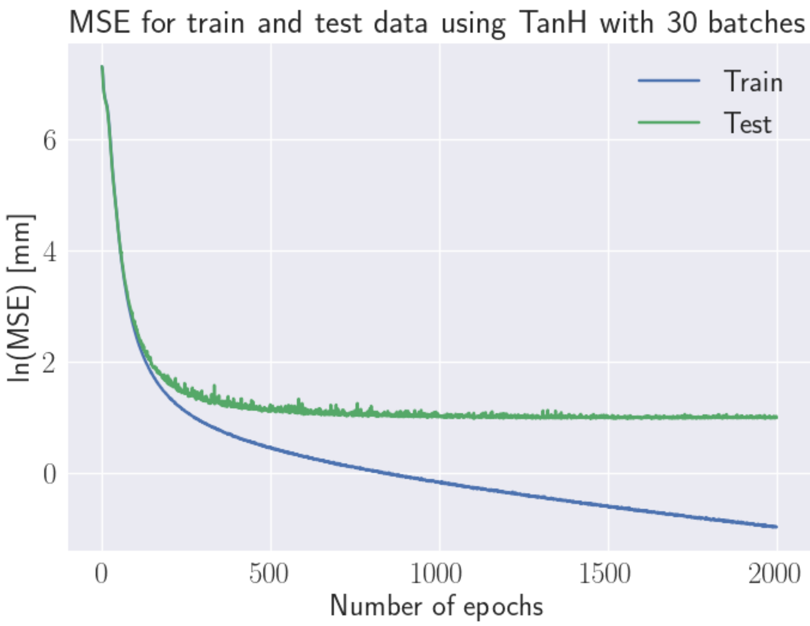

Figure 5.4: The validation accuracy for the simple Feed Forward Neural Network with 10 000 samples with tanh activation function.

5.5 Localizing Multiple Dipole Sources

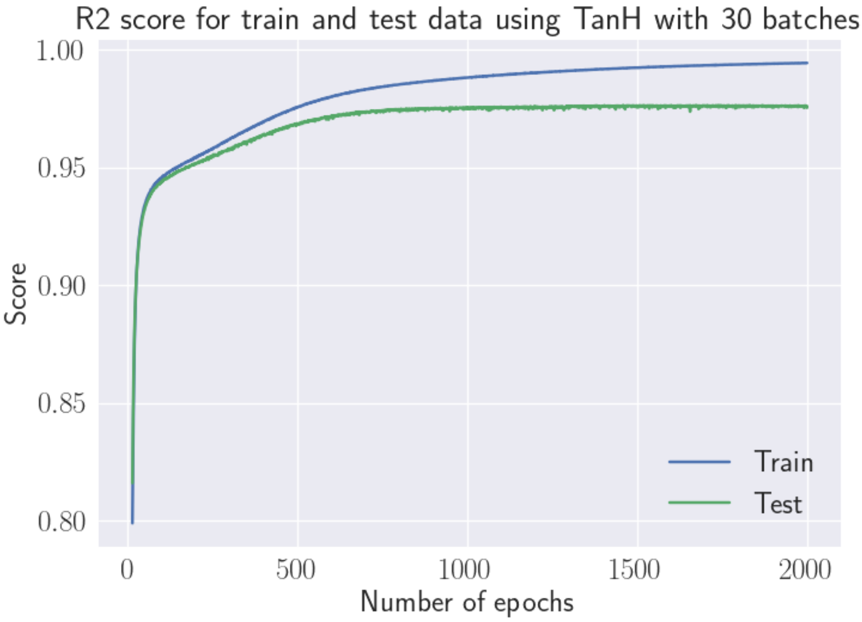

Figure 5.5: The R2 score for the simple Feed Forward Neural Network with 10 000 samples with tanh activation function.

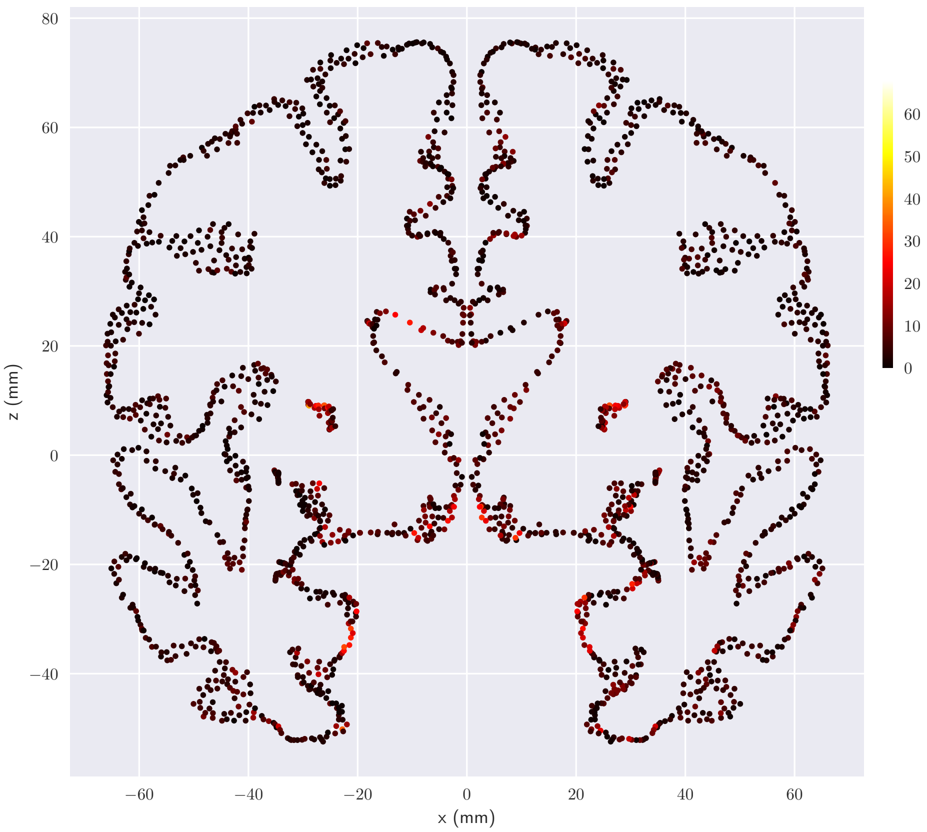

Figure 5.6: The mean squared error of the location accuracy (NN) at different dipole locations in the y cross section, for the simple Feed Forward Neural Network.

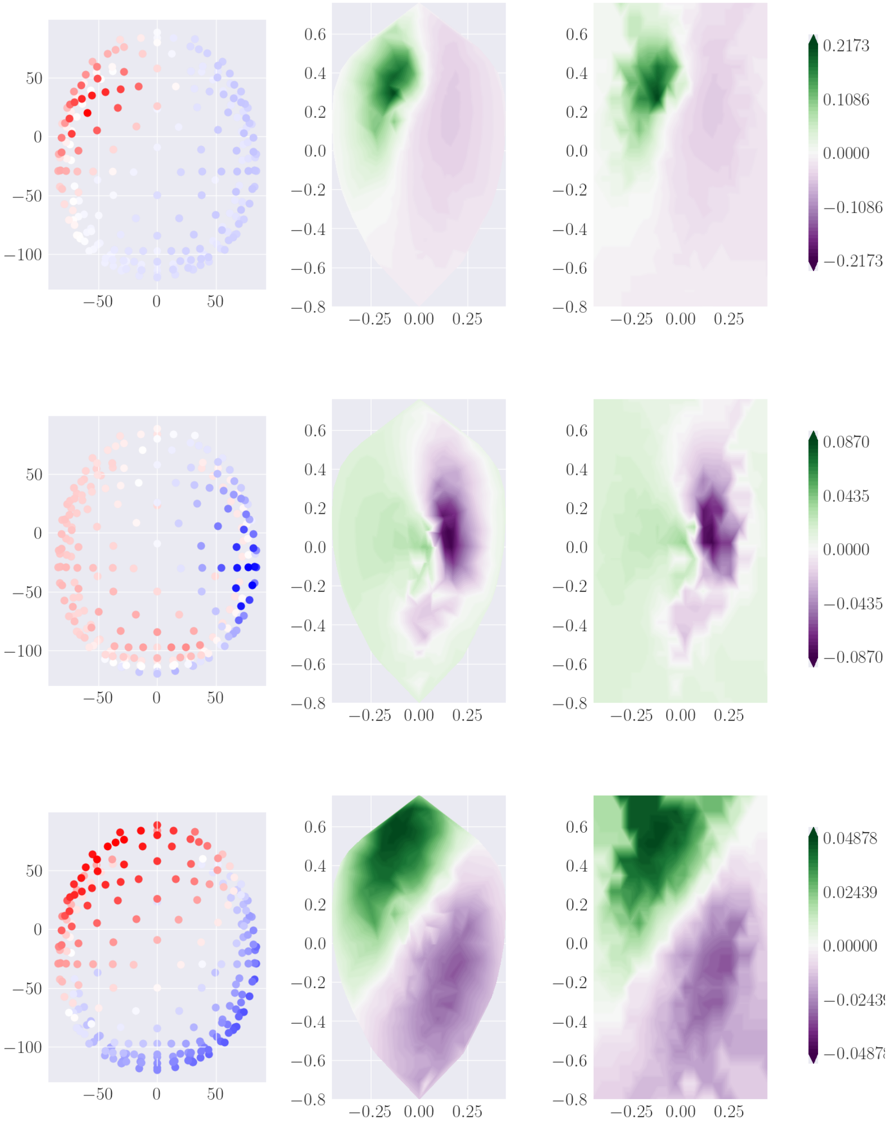

Figure 5.7:
Right: EEG measure for 3 different samples measured in μV.
Middle and Left: Illustration of the interpolation of the EEG data into two-dimensional matrix.

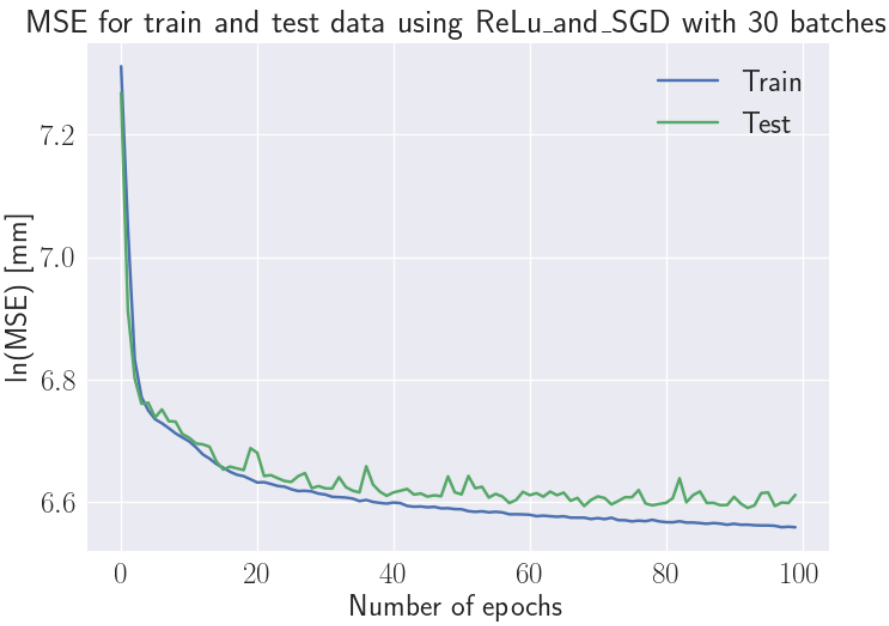

Figure 5.8: The validation accuracy for Convolutional Neural Network with 10 000 samples (20x20 matrix) with ReLU activation function.

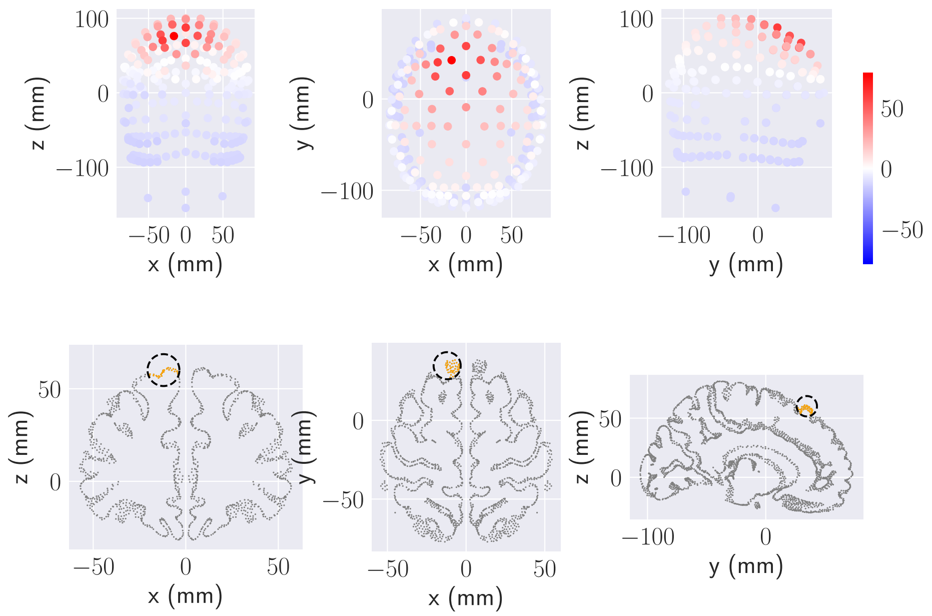

Figure 5.9: EEG for a sample containing a spherical population of current dipole sources with a random center within the celebral cortex. The EEG measure is seen from both sides (x-, z-plane and y-, z-plane) and above (the x-, y-plane). EEG electrode locations are presented as filled circels, where the color of the fill represents the amplitude of the measured signal for the given electrode.

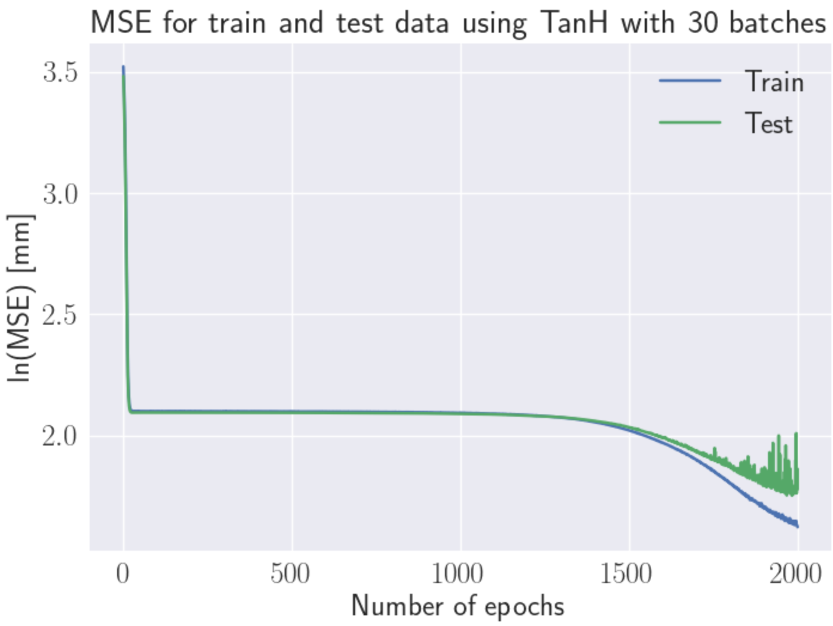

Figure 5.10: The validation accuracy for the simple Feed Forward Neural Network, predicting both center and radius for 10 000 samples, for 2000 epochs, with a learning rate equal to 0.0001.

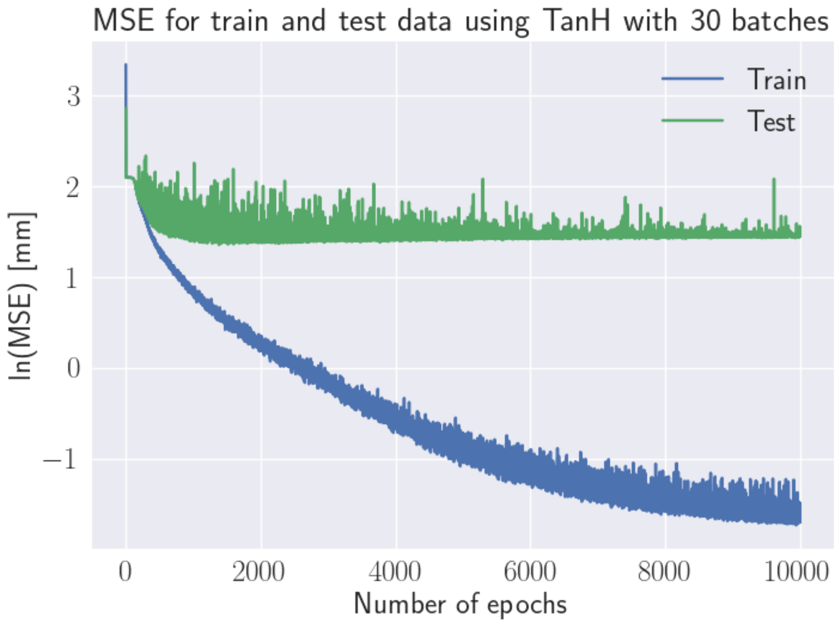

Figure 5.11: The validation accuracy for the simple Feed Forward Neural Network, predicting both center and radius for 10 000 samples, for 10000 epochs, with a learning rate equal to 0.001.

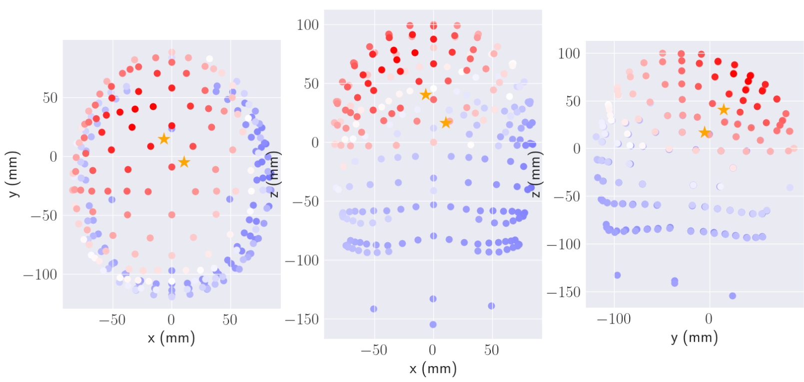

Figure 5.12: EEG for a sample containing two current dipole sources at random positions within the celebral cortex. The EEG measure is seen from both sides (x-, z-plane and y-, z-plane) and above (the x-, y-plane). EEG electrode locations are presented as filled circles, where the color of the fill represents the amplitude of the measured signal for the given electrode. The positions of the current dipole moments are marked with yellow stars.

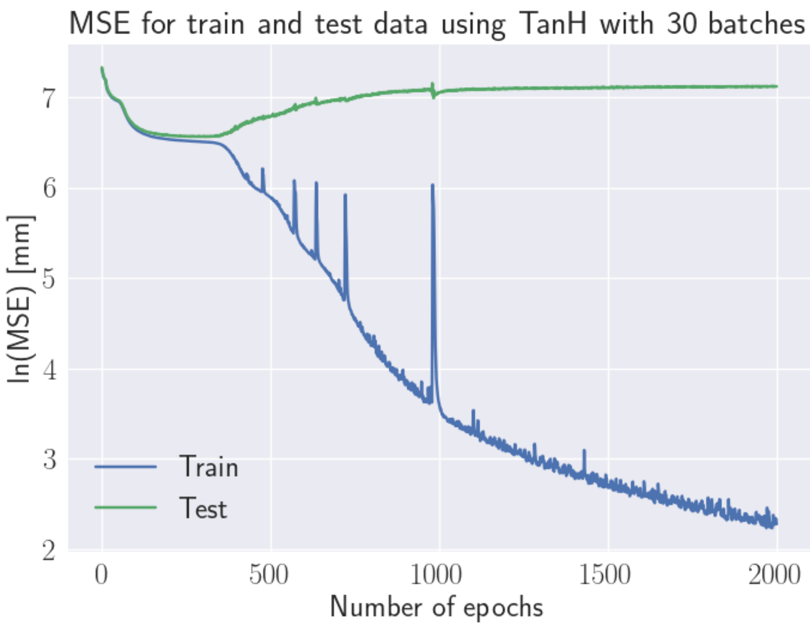

Figure 5.13: The validation accuracy for the simple Feed Forward Neural Network, predicting two current dipole sources.