Analysis of Cortical Connectivity using Hopfield Neural Network

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Abstract: There is striking similarity in the connectivity between perceptrons in an Artificial Neural Network and neurons in brain. Therefore it is a natural logical step to investigate cortical connectivity using Artificial Neural Networks. Present approaches to ascertaining cortical connectivity, e.g. Structural Equation Modeling between various regions of interest (ROI) in the active brain are–tedious and time-consuming . For example, modeling the connectivity of a large number of brain regions often involves numerous parameter changes to achieve a good fit. Functional Magnetic Resonance Imaging (fMRI) is increasing recognized as a standard technique for brain mapping. This study explores the utility of a Hopfield Neural Network to determine cortical connectivity in an fMRI data set.

Introduction:

Artificial Neural networks are being widely used in medicine in general and in Neuroinformatics in particular. Neural networks or artificial neural networks are based on the fact that perceptrons in neural networks simulate the neuronal architecture in the human brain.

In human brain, when there is an activation of region in response to a stimulus, a neurotransmitter is released into the synaptic cleft. Depending on whether the neurotransmitter is inhibitory or stimulatory, the neurons will fire. Similar theory is adapted while studying neural networks. In an artificial neural net, the network architecture is constructed whereby each node represents a synapse. When the total value of an input reaching any node is positive, an output is generated, whereas no output will generated when the input is below the set threshold.

fMRI has come to be recognized as a very important technique in analyzing functional brain activity. fMRI data are acquired as the subject performs some cognitive, sensory or motor task and the data displayed as a colorized map of active regions overlaid on MR images. An important step is to determine how these activated regions are functionally connected during performance of a particular task. Structural Equation Modeling (SEM) is now being widely used as statistical tool to find connectivity between various regions of the brain. However, there are a number of limitations to SEM. SEM techniques are time consuming and tedious. SEM is based on multiple regression techniques to compare a connectivity model based on the observed data to a connectivity model based on hypothesized or known neuroanatomical models. Fitting models containing a large number of brain regions, for example, often requires multiple parameter changes, or changes to the model, to achieve a good fit. Moreover, as research extends into higher cognitive functions, neuroanatomical animal models are of limited value in guiding these decisions [1]. Neural networks may offer advantages to circumvent some of these limitations in SEM. In particular, neural network techniques may provide increased computational speed for larger data sets, and the ability to efficaciously determine the effects of changing connectivity weights in one region of a large network. This paper presents a plausible neural network, which can simulate the way different areas in brain are connected while performing sensorimotor object exploration tasks.

Purpose:

Our purpose in this investigation was to simulate the cortical networks using Artificial Neural Networks during manipulation of objects of differing geometry in the absence of visual input. The question we wished to address was whether the cortical connectivity model obtained using Artificial Neural Network would be consistent with the model obtained by Structural Equation Modeling.

Materials and Methods:

Four healthy right-handed adult human subjects (3M, 1F) were imaged using Functional Magnetic Resonance Imaging (fMRI) techniques. Subjects were imaged on 1.5T G.E. Horizon Echospeed MR system using a standard quadrature "bird-cage" head coil. Images were acquired using conventional BOLD (Blood Oxygen Level Dependent) techniques with the following acquisition parameters: TR/TE = 4000/60; 64 x 64 matrix, 24 cm FOV, 5 mm slice thickness, 90^0 flip angle A total of 28 slices in the axial plane were acquired for each task in each subject Subjects manipulated a total of four objects, using an event-related paradigm design. Each subject freely explored a series of wooden objects among the fingers of the dominant hand for 20 seconds. Each object exploration epoch was separated by a 32 second baseline. The objects were 1-2 cm in greatest dimension and consisted of a square, triangle, rectangle and cylinder. Subjects performed this task with their eyes closed to avoid visual input The raw echo-planar data was reconstructed off-line using software routines written in IDL (Interactive Data Language), motion corrected and statistical maps of activation generated with SPM99. Statistical maps were generated with a SPM (Z) threshold set to 3.09 ($p < 0.001$) and the images normalized to Talairach coordinates and overlaid to T1-w images.

Our research work was divided into three steps: Collection of data, Processing of data and Neural Network analysis of data using MATLAB (6.1).

Auto-Associative Neural Network:

The Auto-Associative Neural Architecture used in our study was initially described by Hopfield [2]. The neural network consists of a set of nodes, which are connected to each other and which are arranged in layers; the simplest of which is a two-layer network consisting of an input layer and an output layer. The time delay is assumed to be same for transmission of information from any one node to another. Activation of a node at any particular time is determined by one of the two states: active represented by 1, or inactive represented by 0. The net synaptic input is obtained by the sum of input from all neurons from which it is receiving connections.

Algorithm:

The net synaptic input is determined by the following equation:

$$E_i = \sum_{j*i} w_{ji} \; (2* s_j - 1)$$

where E_i = net Synaptic Input

Sj = State of neuron (active or inactive)

w_{ji} = Weight of connection between neuron *j* and neuron *i*.

Training:

Training of the neural network was unsupervised; the system learns locally and automatically; the neurons adjusted their interconnectivity by adjusting their weights depending on their co-activation. Hebb's rule [3] was used for training which states that connections between two neurons will strengthen, if more often than not the two neurons fire together.

The projections from one neuron to another are called synaptic weights, which can be either positive or negative. Initially all areas were assumed to be connected to all other areas. The values of weights obtained at equilibrium after training the neural network were either positive or negative. Positive weights depicted connectivity between the two regions, were kept in the model and for negative weights; existing literature was referred so as to determine their inclusion in the model.

Results and Conclusion:

The model obtained by auto-associative neural network represents the anatomical connections between areas believed to be involved in object manipulation task. Our study shows that the auto associative artificial neural network model can simulate the way regions of interest (ROI) are connected in cortex. Once the model is trained it can be used to determine connection between various ROIs in cortex, with different data sets.

References:

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