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Face Recognition using Artificial Neural Network.

Tarika Bhutani[1] , Rashmi Arora[2] , Ronal Juneja[3]

[1]Dronacharya College of Engineering, tarikabhutani2012@gmail.com

[2]Dronacharya College of Engineering, rashmiarora081@gmail.com

[3]Dronacharya College of Engineering, ronakjuneja93@gmail

Abstract-

Face is a complex multidimensional visual model and developing a computational model for face recognition is difficult. We present a neural network-based face detection system. A retinally connected neural network examines small windows of an image and decides whether each window contains a face. Numerous functional magnetic resonance imaging (MRI) studies have identified multiple cortical regions that are involved in face processing in the human brain. In this study, we used FMRI to identify face-selective regions in the entire brain and then explore the hierarchical structure of the face-processing network to analyzing functional connectivity among these regions. We identified twenty-five regions mainly in the occipital, temporal and frontal cortex that showed a reliable response selective to faces (versus object) across participants and across scan sessions. Furthermore, these regions were clustered into three relatively independent sub-networks in a face-recognition task on the basis of the strength of functional connectivity among them. The functionality of the sub-networks likely corresponds to the recognition of individual identity, retrieval of semantic knowledge and representation of emotional information.

1. INTRODUCTION-

The face is the primary focus of attention in the society, playing a major role in conveying identity and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize faces is remarkable. A human can recognize thousands of faces learned throughout the lifetime and identify familiar faces at a glance even after years of separation. This skill is quite robust, despite of large changes in the visual stimulus due to viewing conditions, expression, aging, and distractions such as glasses, beards or changes in hair style. [1]- [5] Face recognition has become an important issue in many applications such as security systems, credit card verification, criminal identification etc. Even the ability to merely detect faces, as opposed to recognizing them, can be important. Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by a human brain. Human face recognition has been studied for more than twenty years. Developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. For face identification the starting step involves extraction of the relevant features from facial images.

2. Why Face Recognition using neural network?

Face recognition systems enhance security, provide secure access control, and protect personal privacy. Improvement in the performance and reliability of face recognition. No need to carry any passwords or carry any ID. And we use neural network here because Adaptive learning: an ability to learn how to do tasks. Next one is Self Organisation: An Ann can create its own organization. Third one is it has a remarkable ability to derive meaning from complicated or imprecise data.[6] A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. In the broader sense, a neural network is a collection of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. It is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses. An artificial neural network is a computing system made of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external input. Motivated right from its inception by the recognition. A machine that is designed to model the way in which the brain performs a particular task. A massively parallel distributed processor. Resembles the brain in two respects, one is Knowledge is acquired through a learning process. And second is Synaptic weights, are used to store the acquired knowledge. [9]

3. Structure of a typical neuron

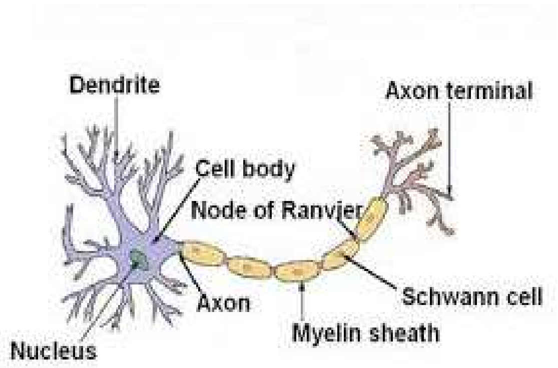

Figure-(1)

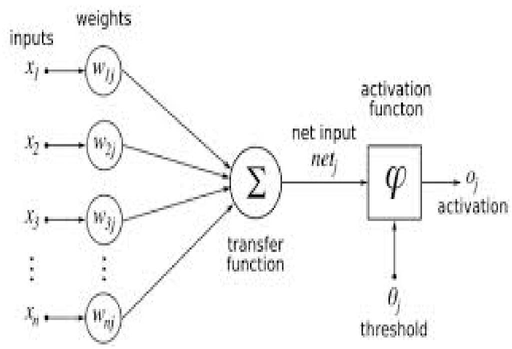

Figure-(2)

Neural network architecture is divided into three networks. One is Single layer feed forward network. Second one is Multilayer feed forward network and third one is Recurrent network.

4. Methods-

i) Detection- Forty-two college students (aged 20-30 years; 18 females) participated in the study. All participants were right handed and had normal or corrected-to-normal visual acuity. Ten participants were scanned seven times over seven consecutive days (i.e., seven scan sessions in total), and the rest of the participants were scanned once. The FMRI protocol was approved by the Institutional Review Board of Beijing Normal University, Beijing, China. Written informed consent was obtained from all participants before the experiment. [7]

ii) Alignment and Normalization- In each session, two blocked-design functional runs were conducted. Each run consisted of blocks of human frontal-view faces, familiar objects, scenes and scrambled objects. Scrambled objects were generated by superimposing a grid over object images and then relocating the component squares randomly. The image of the head is scaled and rotated so that it can be registered and mapped into an appropriate size and pose.

iii) FMRI Data Acquisition- Scanning was conducted on a Siemens 3T scanner (MAGENTOM Trio, a Tim System) with an eight-channel phased-array head coil at BNU Imaging center for Brain Research, Beijing, China. The whole brain FMRI data were collected using a T2*weighted gradient-echo, echo-planar imaging sequence (EPI) (TR=2sec, TE=30 ms, FA=90 degrees, matrix=64*64, 25 slices, voxel size=3*3*4 mm). In addition, MPRAGE, an inversion prepared gradient echo sequence (TR/TE/TI=2.53 sec/3.45 ms/1.1sec, FA= 7 degrees, Voxel size= 1*1*1 mm), was used to acquire 3D structural images.

iv) MRI Data Preprocessing-

fMRI data analyses were performed with fMRI Expert Analysis Tool (FEAT) of FSL). Preprocessing was performed with the default parameters of FEAT, consisting of motion correction, brain extraction, high-pass temporal filtering (0.01 Hz cutoff), spatial smoothing with a Gaussian kernel (FWHM = 5 mm). Then, each run in a session was modeled separately for each participant. A boxcar was convolved with a gamma hemodynamic response function, and its temporal derivative was used to model blood oxygen level-dependent (BOLD) signal changes.

v) Network Analyses on Functional Connectivity-

Here we used the strength of functional connectivity among the ROIs to characterize the hierarchical structure of the face-processing network. First, the time courses of the BOLD signals of all voxels within an ROI in each run were extracted and averaged across voxels. Second, to remove fluctuations from head motion, six parameters obtained by rigid body corrections for head motion with their temporal derivatives were regressed out from the averaged time course. Third, the residual time courses of all face blocks in the session from an ROI were normalized to *z* scores, which were then concatenated as one continuous time course. Because there were eight data points in a face block (i.e., 16 sec per block with TR being 2 sec), four face blocks in a run and two runs in a session, there were sixty-four data points in total in the time course of an ROI of a participant. Fourth, for each participant, a matrix on functional connectivity was created by calculating Pearson correlation coefficient (*r*) between the time courses of each pair of ROIs. The matrices were then averaged across participants.

vi) Results

Twenty-five Face-selective Regions are Identified in the Entire Brain

Because there is considerable amount of variability in face-selective activation across individuals and across scan sessions, regions that are truly involved in face processing shall meet three criteria: (1) consistent anatomic location across individuals (cross-subject reliability), (2) replicable selectivity for faces across sessions within an individual (i.e., cross-session reliability), and (3) selective responses for faces but not for a variety of non-face objects.

vii) Discussion

In this study, we characterized the face-processing network comprised of face-selective regions in the brain. We first identified twenty-five regions showing reliable face-selective activation across participants and across scan sessions. The functional connectivity analysis revealed that these regions were clustered into three relatively independent sub-networks. Importantly, the IOG may serve as an entry node of the face-processing network, as the functional connectivity between the IOG and the rest of the regions were significantly decreased when the participants switched from the face-recognition task to the object-recognition task. In short, our study provides some of the first empirical evidence of the face-processing network throughout the brain, inviting further studies on face recognition from the network perspective.

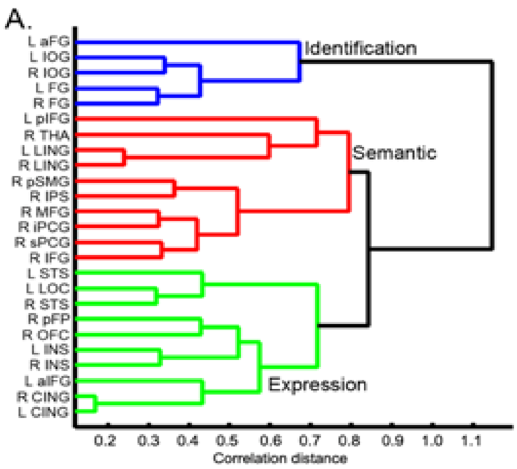

Figure-(3)

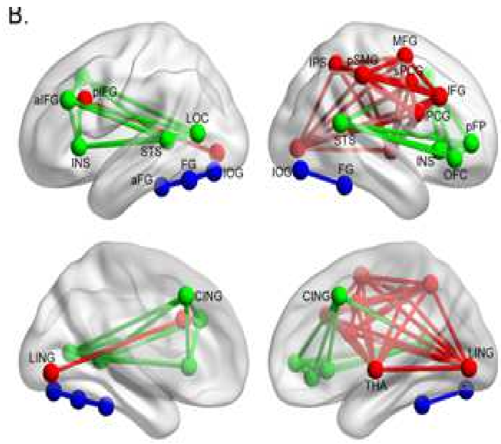

figure-(5)

5. Reference-

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