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Whole brain connectomic architecture to develop general artificial intelligence

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Abstract

Whole Brain Connectomic Architecture (WBCA) is defined as a software architecture of the artificial intelligence (AI) computing platform which consists of empirical neural circuit information in the entire brain. It is constructed with the aim of developing a general-purpose biologically plausible AI to exert brain-like multiple cognitive functions and behaviors in a computational system. We have developed and implemented several functional machine learning modules, based on open mouse connectomic information, which correspond to specific brain regions. WBCA can accelerate efficient engineering development of the intelligent machines built on the architecture of the biological nervous system.

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Keywords: connectome, general artificial intelligence, whole brain architecture, empirical neural circuits, efficient engineering

1 Introduction

Competition for development of artificial intelligence (AI) is intensifying worldwide. The development of the artificial intelligence field is progressing at a remarkable speed, primarily because most major IT companies are involved. The growth in this field was evidenced at the most recent NIPS conference, which recorded the largest ever number of participants. We demonstrate one of the efficient means of creating artificial general intelligence (AGI) by adopting the whole brain architecture (WBA) approach (Figure 1) (Yamakawa et al., 2016). We believe a unified platform is required to develop AGI. In this paper, we describe the development of WBA based on the connectome structure, which is a neural circuit wiring diagram.

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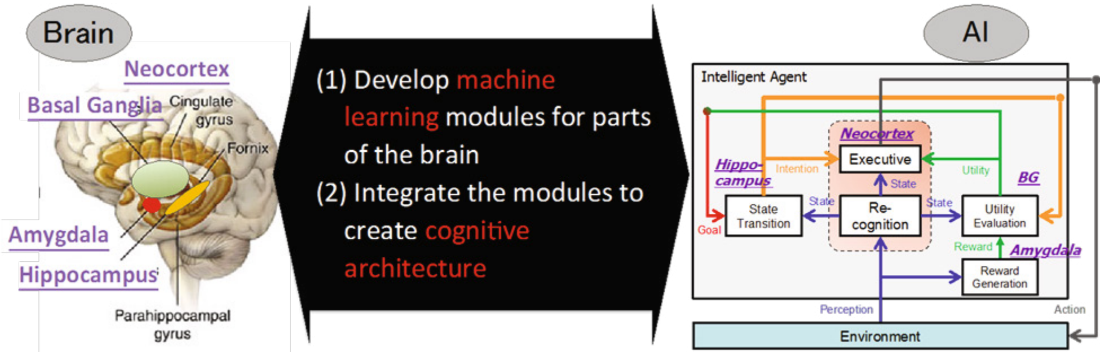

Figure 1: Whole Brain Architecture approach. The diagram represents brain-like AGI development scheme according to an entire brain architecture with multiple machine learning modules implemented based on the actual connectomic morphology.

The static reference architecture was developed based on the knowledge of connectomes, neural wiring diagrams, as Whole Brain Connectomic Architecture (WBCA) and we used it to develop the base of WBA. We collected connectome information focusing on a wide range of mesoscopic data with spatial resolution capable of visualizing nerve cells to some extent and used this to construct WBCA. It is posited that AGI can be developed efficiently by constraining the combined repertoire of machine learning constituting artificial intelligence by connectome. WBCA is hierarchically described because the descriptive granularity required by AGI function, the developer's preference, the computer performance, etc. is different. For example, descriptions at the level of the cerebral organ such as the cerebral cortex, the hippocampus, and the basal ganglia are assumed as the coarsest grain size, and each is described as a machine learning instrument as a brain organ module.

Many gains have developed in recent years that could solve many problems if sufficient learning data exists. Therefore, research on (AGI) technology which enables one AI agent to acquire various problem-solving skills through learning is gaining momentum worldwide. In building AGI, a cognitive architecture that is a framework of the system is required. In the AI field, several cognitive architectures have been built based on various design concepts, but there is no specific design concept that is dominating others in the field. With this backdrop of multiple design concepts, it is difficult to construct general purpose software with a single design philosophy. In short, in a general-purpose system, it is not possible to adopt a standard design strategy that will decompose objects into functions and implement them to realize that function.

On the other hand, knowledge of neuroscience is rapidly increasing, so attempts to create correlating artificial intelligence are also increasing. Since the brain is the only real existing intelligence, it is easy to obtain consensus among researchers with its architecture as the completed goal. This is an effective scaffold for collaborative work that could integrate individual technologies. In this approach, the brain realizes the function by combining machine learning instruments that each have well-defined functions, and imitates them. Machine learning that is artificially constructed is based on the hypothesis that it is possible to build a general-purpose intelligent machine with human-level or higher ability by combining vessels. Per this hypothesis, the construction of the AGI system is broken down into the development of machine learning modules for each brain organ, and integrating these modules based on the brain type cognitive architecture. Attempts to learn from the brain to build artificial intelligence are not new, but until now, there have been two major problems in promoting brain-type artificial intelligence. However, these issues have possible solutions.

First, deep learning has appeared in such a way as to imitate to some extent the cerebral neocortex playing a pan-important role. Second, research on the connectome, which is the basic information of the cognitive architecture of the whole brain, has greatly advanced in the field of neuroscience. The neuron model used in the current artificial neural network is exhibiting various functions despite being a rather simple model without internal structure. Given these technological conditions, there is the possibility of making artificial intelligence with simple cognitive functions like humans based on neurons. Therefore, in this research, we focus on the relatively rough, brain mesoscopic connectome, and based on this, we construct WBCA, which is the reference model of whole brain architecture and the basis of brain type information processing research.

In the WBA approach, the aim is to ultimately mimic the human brain. To start with, though, we first prepare WBCA from information such as connectome about rodents that have a rich accumulation of neuroscientific knowledge. Rodent intelligence does not reach the capabilities of human intelligence, including language etc., but the brain architecture that supports higher brain function is highly homologous, and research results in rodents are useful when stepping up to more complex systems, like humans. Specifically, we will aim for 100% coverage of the four main parts related to higher cognitive function (the neocortex, the thalamus, basal ganglia, and the hippocampus). Then, by combining artificial neural networks such as deep learning, we implement some cognitive functions of the brain and conduct practicality and functional verification as a research and development platform.

Neuroinformatics improves the capability by organizing the information obtained experimentally, assuming medical application, etc. This creates the need to handle information in detail and exhaustively. On the other hand, WBCA focuses on specific neuroscience knowledge to obtain a framework for linking machine learning, creating good prospects for engineering researchers and engineers. For at least the neocortex, it is reasonable and realistic to adopt a mesoscopic connectome, which defines the coupling between regions, as an architecture. Because the function of individual areas in the new cortex is determined mainly by the unique combination of the source field and the target area to be connected (connection fingerprint), the layer unit of deep learning dealing with visual information corresponds to the area of the visual cortex This can be attached using WBCA, which forms the basis of the architecture of the whole brain.

2 Representation of Brain Region Interconnectivity

2.1 Preparation of Strength Matrix between Brain Areas

The first task is to collect connectome data from existing databases and academic papers. The database with the most information accumulated in the connectomic data is the Allen Mouse Brain Connectivity Atlas (Oh et al., 2014) provided by the Allen Institute for Brain Science. Therefore, using this database as a template, we created the basic data section of WBCA focusing on the connectivity information between brain regions. The Allen Mouse Brain Connectivity Atlas stores connectivity data between 295 brain regions. Currently, 2279 experimental data are stored on the database, and all experiments are injections of stain solution capable of tracing nerve cells into each brain region. From there, 104 regions corresponding to the cerebral neocortex, the thalamus, the basal ganglia, and the hippocampus are selected, and the extent to which the brain region of the projection source and the brain region of the projection target is nerve-projected is extracted. Since the number of voxels in the stained area is registered in the database, the nerve coupling strength from the brain region of the injection destination is calculated based on the number of voxels of the projection destination. By using the API distributed at Allen Laboratories, we automatically comprehensively acquire neural connectivity data by scripts etc. and metricize the binding strength between each brain region to make it the basis of WBCA (left in Figure 2).

2.2 Preparation of Neocortical FF / FB Directional Matrix

With regard to the connectivity of the cerebral cortex region, determining the direction of feedforward / feedback (FF / FB) is extremely important for operating the deep learning model of the

WBCA. Therefore, we also use the Allen Connectivity Atlas to identify the FF / FB relationship between each region of each cerebral cortex. Since there are 40 neocortical areas on the database, a reasonable FF / FB relationship was determined for these areas. The method of determining the FF / FB relationship was adopted from the method of Markov et al, 2014. This method quantifies whether the staining solution migrates to the upstream side or the downstream side of the granule cell layer when the staining solution is injected into the neocortex. The ratio is defined as SLN (Supragranular Labeled Neurons). In the Allen Connectivity Atlas, it is possible to acquire a list of experimental data on the projection by selecting the projection source and the projection destination, so that it is possible to calculate the FF / FB property of the neural projection appropriately from that experiment data. An example of analysis of the FF / FB property of the neocortical area 38 is shown by randomly selecting one piece of data from the appropriate available data (right in Figure 2).

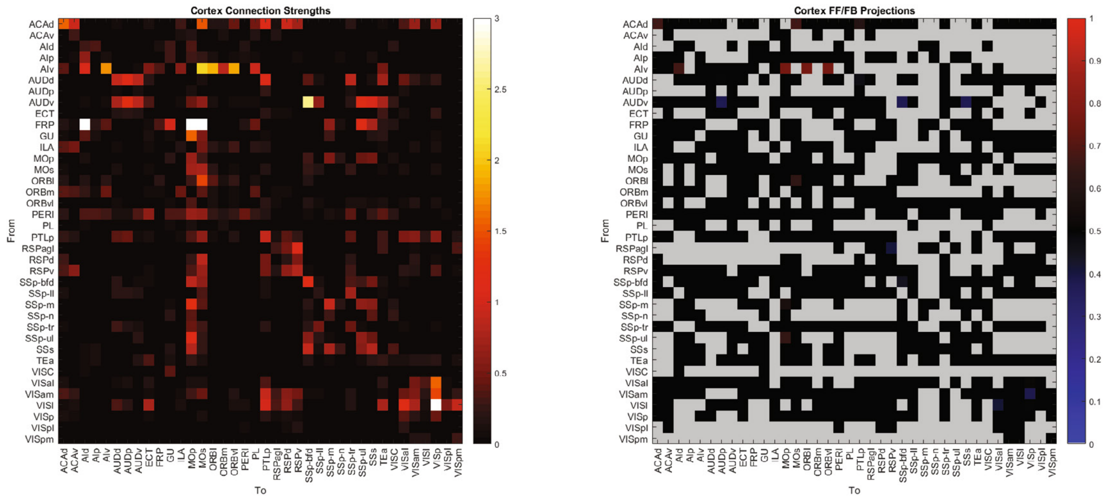

Figure 2: Matrix of binding strength (left) and FF / FB directionality (right) between each neocortical area calculated from Allen Mouse Connectivity Atlas at http://connectivity.brain-map.org/

3 Creation of Cognitive Architecture and Functional Verification

Using the results of bond strength analysis and FF / FB directional analysis between neocortical regions, we constructed a brain architecture to develop cognitive function. Within the brain architecture, we constructed a deep learning model along the FF / FB directionality between the neocortex and verified the functionality using the specific cognitive model described below.

3.1 Description of Brain Architecture

The neural connectivity matrix that defines the connection between the brain regions is described by the machine readable architecture description language BriCA (Takahashi et al., 2015) to describe the network structure. This makes it possible to build a cognitive architecture while linking modules without depending on a specific computer environment (computer language, OS, etc.). Also, by separating the structure and procedures, it is easy for developers to refer and share structures.

3.2 Calculation Platform for Brain Architecture

As a computing platform for the implementation of the brain architecture, multiple modules called BriCA exchange signals having values as numerical vectors (simulating signals flowing through a bundle of nerve axons). BriCA can asynchronously combine and execute multiple machine learning modules.

3.3 Agent Simulation Platform

The cognitive architecture exerts its cognitive function as an agent interacting with the outside world. To verify the cognitive function, we will incorporate the cognitive architecture into the agent in a simulation environment and perform the simulation. Here, we use an environment called LIS (Life in Silico) (Nakamura and Yamakawa, 2016) as an agent simulation platform. LIS makes a game with the game engine Unity and the agent built in the cognitive architecture.

3.4 Verification

Using the WBCA as a basis for the whole brain and focusing on specific cognitive functions, we created a cognitive architecture as software implementing a machine learning module on BriCA and verified whether the cognitive model works in the virtual environment simulator. The targeted cognitive functions are based on spatial memory (Morris water maze), working memory (2~8 direction radial maze) etc., which are commonly used in mouse behavioral experiments. As a machine learning algorithm used for verification, Convolutional Neural Network (CNN) and reinforcement learning are used. Since the cognitive architecture is represented by WBCA, there is a strong connection with the constraints on connectivity. We verify that the machine learning framework functions on a static foundation in which a structural module is fixed, called a mesoscopic connectome structure. The minimum unit as a functional module is defined as the minimum size of the brain region in which the neuronal connection relation is recognized by the Allen Connectivity Atlas, and combinations thereof are made in consideration of the actual projection relation. The size of the final functional module makes it possible to flexibly change within the applicable range of the machine learning frame. In the evaluation method of cognitive function, we introduce criteria (time to attain the goal, etc.) that are almost equal to that of usual mouse behavioral experiments and observe how closely the computer mouse approaches the learning behavior of the actual mouse. The operation verification of cognitive function is performed by installing WBCA written in BriCA language on BriCA and incorporating it in the agent in the virtual environment simulator LIS.

3.5 Verification Environment and Agents

In this paper, we constructed the agent composition and learning environment based on the experiment of Manita et al. 2015 on haptic sensations, especially tactile and memory related to texture of the surface. This paper aims to reproduce this experiment in virtual space. We installed two cameras inside the agent. One camera functions as the vision of the agent and the other replaces the tactile sense of the agent. The camera that substitutes for vision is installed on the front of the head of the agent and represents the viewpoint of the agent. Through this camera, we can observe the state in the space where the agent is located. A camera representing tactile sense is installed at the feet of the agent and observes the floor surface which changes as the agent moves. The resolution is 227 x 227 for the vision camera and 10 x 10 for the tactile camera. The different resolutions of the cameras were determined on the assumption that the tactile sense with respect to the uneven surface can function at a lower resolution than the camera for visual sense. The agent learns based on its experience with these two conditions and obtains a reward.

We created an environment where the agent is placed in a labyrinth designed in a "Y" shape where the surroundings are covered with walls. The reward is arranged at the tip of the Y-junction maze. At the branch point, a wall that blocks the view of the reward is installed so that the reward cannot be seen from the viewpoint camera of the agent at the branch point. The agent can go to either branch at the Y-junction, and obtains a reward if it chooses the right one. The agent can perform three kinds of behaviors: agent left, clockwise, and forward.

Two kinds of uneven floor surfaces were installed in front of the branch point, and the agent estimates the position of the reward based on the floor surface. The reward appears in one of the ends of Y depending on the floor surface. Unevenness on the floor surface is expressed as shades of gray scale image patterns to simulate tactile cues. The shading is expressed in 256 steps from 0 to 255; the closer to 0, the flatter the surface, and the closer to 255, the more convex the surface. Different floor surfaces randomly appear with 50% probability. Each trial has a fixed number of steps, and is designed to automatically return to the starting point when reaching more than a certain number of steps. The agent updates the evaluation function based on the time it takes to acquire the reward and the selected action, and then learns to obtain the reward more quickly by repeating the trial.

4 Conclusion

The first step in conducting this approach is to construct WBCA as the basis of the WBA. WBCA was constructed as a framework of intelligence that solves problems by combining new expressions and knowledge acquired by machine learning. We are developing an algorithm that realizes each brain cognitive functions reliably and efficiently. We hope to realize a flexible artificial intelligence system that follows WBA. Once the framework is laid, many machine learning and artificial intelligence experts (e.g. engineers, researchers) can focus on the local network and multiple machine learning modules It becomes possible to build an artificial intelligence system combining the work of many. Thus, using WBA makes it conceivable to efficiently execute distributed cooperative development in the presence of connective constraints It also is possible to promote research and development of AGI under this uniform framework.

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