Designing a Robotic Platform Controlled by Cultured Neural Cells

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Abstract

Robot experiments using real cultured neural cells as controllers are a way to explore the idea of embodied cognition. Real cultured neural cells have innate plasticity and a sensory motor coupling is expected to develop the neural circuit. We designed a system in which a robot moving in a real environment is controlled by cultured neural cells growing on a glass plate attached to a High-Density Microelectrode CMOS Array(HDMEA). The IR sensors on a robot will feedback onto the neural cells through HDMEA and the activity of the neural cells will be read again by HDMEA and sent back to determine the speed of the robot. Most of the previous works have used the relatively low-density multi-electrode array for recording and stimulating the neural assembly. Our system has the advantage of a high-density spatial and temporal array so that we can precisely detect which neurons get fired and suppressed. A preliminary finding from the experiment is that synchronized neural activation is retained in cultured neurons even after detached from a robot.

Introduction

Recently, it became easier and popular to study the coupling between a robot and a network of cultured neural cells. In those studies, the sensory information coming from the moving robot is used to stimulate the neural cells, and the resulting activities of those determine the speed of the motors driving the robot. This is what is called a "closed loop" experiment. We believe that it is critical to conduct such closed loop experiment for revealing biological memory and adaptability with respect to embodiment. Behavior is not a one way function of sensory inputs but behavior assimilates by itself.

For example, Bakkum et al. (2008) have proposed a new method to train a biological neural cells to achieve a desired pattern for multiple stimulus. Kudoh et al. (2008) have proposed another learning method using a cultured neural system that incrementally learns to respond in a particular way to a particular input. One drawbacks of those studies is that their microelectrode array has not enough space resolution, so that it is difficult to stimulate/detect a single neuronal state. The other drawback is giving an external evaluation function that enables a coupled neuro-robot system to work. Such evaluation function should be developed from the neuro-robot itself, namely, we have to develop neural self-organization of sense-making behavior with a mobile body. In order to overcome those drawbacks, we use a recently developed high density CMOS array (HD-MEA) capable of detecting the activity of individual neurons with high precision. With HMDEA, we can measure the spatio-temporal neural pattern with a higher precision and reveal how neural plasticity and memory can self-organize the sense-making behavior in a given environment.

Method

A simplest task we seek here is avoiding or reaching behavior of the robot without putting further constraints.

The main components of this system are the HDMEA monitoring the culture of neural cells, the robot in its arena and the interface connecting them. The system gathers the signal from the robot, stimulates the neural cells by using HMDEA and sends the motor output signal to the robot. This way, the robot and the neural cells form a closed loop. The HDMEA we used in this study provides a higher spatio-temporal resolution compared to previous studies [Frey et al. (2010)]. Thus we can monitor all the neural activities by using less than 126 cultured neural cells and the adequate electrode channels. For the moment, we can stimulate at most two cells at a time out of 126 channels available. The sampling rate of HDMEA is 20kHz. A software MeaBench developed by D. Wagenaar [Wagenaar et al. (2005)] is used for recording and detecting spikes and controlling the whole system.

We used Elisa-3 (Manufactured by CGtronic) as a mobile robot. Elisa-3 is a circular small robot of 2.5 cm radius and it has two independently controllable wheels. In this experiment, we use the front right and front left distance sensors as sensory stimulation for the neural cells.

We chose two excitatory neurons as left or right input-neuron for receiving the stimuli. Stimulation to the neural cells is determined by the in-take sensor inputs of this robot. We designed it as that the closer a robot approaches a wall and the higher the sensory inputs become, the more frequently the neurons are stimulated.

We selected 20 neurons as output-neuron within the vicinity of each input-neuron for computing each left and right motor outputs. The left and right wheel speeds are computed based on the number of firing of the output-neurons that is integrated every 100ms. More practically, we compute the left and right wheel speeds V_l and V_r as follows:

$$V_{l,r} = \sum_{i \in \mathbf{N_{l,r}}} \omega_i v_i + C$$

These virtual neural states v_i take the positive integers which are equal to the number of spiked neurons over a given time interval, and summed up with the fixed weight ω_i. Finally a positive constant C is added. $\mathbf{N_l}$ and $\mathbf{N_r}$ are the number of left and right output-neurons.

In this time, as ω_i is negative value and C is positive integer, the robot move forward when output-neurons are not active and the higher the activities of output-neurons becomes, the slower the speed of the forwarding and finally robot move back. The cultured neurons were prepared from the cerebral cortex of fetus of Wister rats.

Result

We conducted 10 minutes robotic experiments in a 60cm by 60cm arena and recorded both the neural activity and the behavior of the robot. The neural spiking patterns are recorded in the pre-experiment, during the experiment, post-experiment and an hour later after the experiment. They are shown in Figure 1. The neural activity of the pre- and post-experiment are different and it seems that the influence of the closed-loop experiment lasts at least for one hour after the experiment.

We then evaluated the temporal changes of the wall avoidance frequency (how many times a robot can avoid crashing into a wall) and computed the time evolution of the correlation coefficient between the neural firing rates in Figure 2. It is indicated that the correlation is inversely correlated with the wall avoidance frequency.

Discussion

We report the design of a robot experiment with a cultured neuron using HDMEA and the preliminary result of the experiment. The results indicate that the correlation of activities of each neurons is inversely correlated with the wall avoidance frequency. Furthermore, we observed that the effect of the stimulation remains for at least 1h after the experiment. It is interesting in terms of memory or learning in the neural network. However, as these are the preliminary results, we need more experiments and analyses.

The system we proposed has a high-resolution that can monitor individual neuronal activities. Therefore, we expect the more detailed investigation about relationship of dynamics of neural network, memory or learning with embodiment. We plan to do more detailed studies such as analyzing

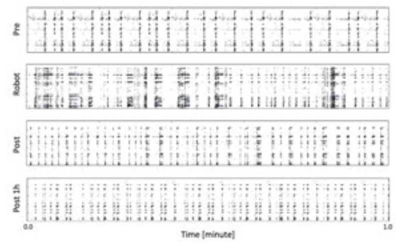

Figure 1: Raster plot of the neural activities of pre-experiment(top), during the robot experiment (2nd), the post experiment(3rd) and the post one hour (bottom). The vertical axis is the index of neurons and the horizontal axis is time steps (of 1 minutes tics).

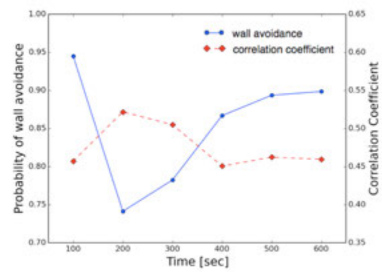

Figure 2: The probability of wall avoidance of robot (blue) and the correlation coefficient of the neural activity (red).

temporal-spatial patterns of neural activities or estimating functional aspects of the network.

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