Neuro-robot Vitroid

- Living neuronal network with physical embodiment by a miniature moving robot

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ABSTRACT

We developed neuro-robot system with closed-loop interaction between the circuit of living neurons and outer world interfaced by a miniature-moving robot. Using the system, an interface for interaction between neurons and outer world can be evaluated. We call the concept that LNC is the central processing unit of the neuro-robot "Vitroid". As an example of interfacing algorithm between neuronal activity and robot behavior, we implemented SOM-based algorithm to generate robot behavior. The winner nodes of SOM were gradually gathered together by each category during a robot running, suggesting the mapping between inputted data and corresponding representative position in the clustering space is correctly updated during the robot behavior. In addition, SOM-Vitroid succeeded in generation of collision avoidance behavior and animal-like autonomous behavior.

Categories and Subject Descriptors

BBC [**Brain and Body Computing based on Embodied Knowledge**]

General Terms

Algorithms, Design, Experimentation,

Keywords

Embodiment, Neuro-robot, Living Neuronal Network (LNN), Multi-Electrode Array (MEA), synthetic intelligence.

1. INTRODUCTION

Embodied Cognitive Science (ECS) is promising approach to generate synthesized biological intelligence and it emphasizes the critical roles of a body on intelligence [1,2]. According to the concept of ECS, The robot does not always require complex algorithms to perform biological behavior. For example, a moving robot with two light sensors connected to actuators located on ipsilateral side of the sensor performs light avoiding behavior if the sensor promotes speed of the actuator. On the contrary, a moving robot with the sensors connected to contralateral actuators performs phototaxis (Figure 1a)[3]. This simple reflex circuit is common among animals and it is also enough to perform complex behavior. Fish has a pair of Mauthner neurons; they activate the muscles at only the contralateral side of the body, while the muscles at the other side of the body relax (Figure 1b) [4]. This chiasmal circuit simply generates avoiding behavior, without any symbol manipulation. The relationship between brain network and peripheral system provides embedded behavior. Thus, design of connections between brain and body is the base of the animal behavior. The connections are genetically defined and designed by evolution in the case of animals. Therefore, neuronal network with suitable connection to artificial body is considered also to perform a certain purposive behavior. The living neuronal circuit (LNC) with closed-loop interaction, interfaced by artificial robot body, is called as neuro-robot. Neuro-robot is the novel field of intelligent robotics, which exemplifies the ECS concept with living neuronal circuit. The concept of integration of a small moving robot and a living neuronal network was firstly proposed by Potter's group as Hybrot [4]. We also developed a neurorobot "Vitroid" with hippocampal-dissociated culture [5-7]. In Vitroid concept, the living neuronal network is regarded as a central processing unit, just like brain is the central component of nervus system (Figure 2). Therefore, the default instinctive behavior of the robot is embedded in the relationship between the neuronal network and peripheral system of the Vitroid, artificial robot body. The connection between LNC and the robot body is virtually achieved by processing algorithm to transcode the neuronal activity. Various algorithms are considered as the candidates for the Vitroid system. For example, we previously the Vitroid implemented by fuzzy pattern template (FPT) matching method [8,9]. The system has been introduced as "Biomodeling system"[10]. In this paper, we newly propose Vitroid with Self-Organization-Map, toward the neuro-robot with flexible response to the novel situation.

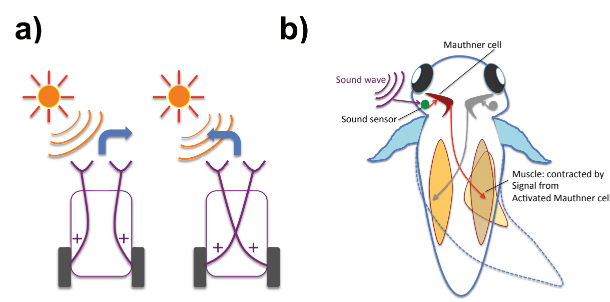

Figure 1. a) Examples of simple robots performing biological behavior. b) Example of the embodiment of fish.

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2. Concept of Vitroid

The most principal concept of the Vitroid is that the LNC is the central master component. Methods for preparing rat hippocampal dissociated culture system for LNC and for measuring electrical activity by extracellular potentials multisite recording system were previously reported. Refer to these papers [8,11,12]. The LNC is not intendedly manipulated, and LNC is left to be changed only by interaction between LNC and outer phenomenon. Responses of LNC against an input from outer world are fluctuated by internal autonomous activity. We consider that the fluctuation includes certain information. Instead of discipline the LNC to perform ideal response, we designed the connection algorithm between LNC and the robot body to perform the ideal behavior (Figure 2). The system has two programs communicating each other via TCP-IP protocol (Figure 3). BrainInterface is an interface of a living neuronal network and data socket server, including an event detector of neuronal activity. Client is an interface of a robot body and data socket server, including behavior generator for a robot body. These two programs composed Neuro-robot Interface in Vitroid concept.

2.1 Mapping to dynamic category

LNC performs mapping the information from real world to spatiotemporal pattern of neuronal activity. The mapping procedure includes modification of the inputted information. Various strategies are considered for decoding neuronal activity pattern to the situation of inputted phenomenon, and mapping strategy with dynamic category is proposed in this study. Neuronal activity patterns are classified in advance and linked to the specific behavior of the robot (Figure 4). A certain activity

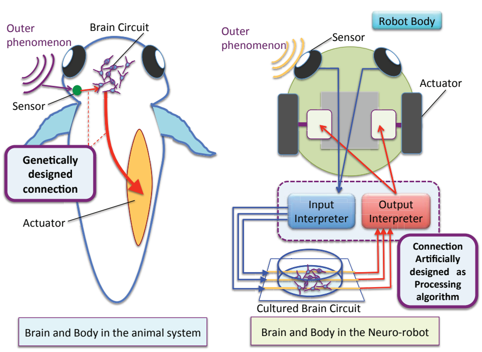

Figure 2. Vitroid concept.

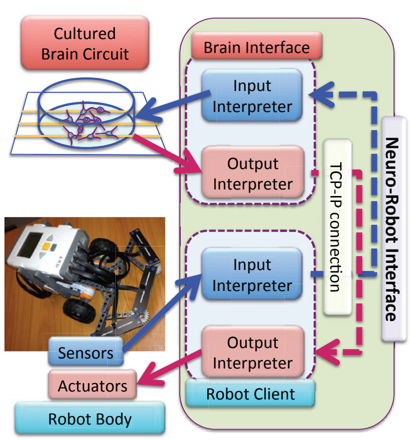

Figure 3. Schematic diagram of Vitroid.

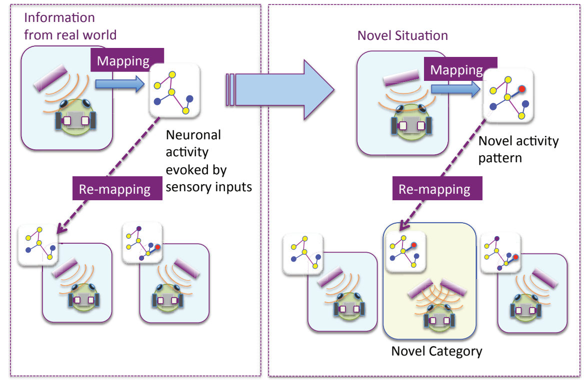

Figure 4. Strategy of mapping to dynamic category.

pattern evoked by input is compared to pattern templates and the certain category is selected as decoded situation, according to the similarity between the electrical activity patterns and templates. Thus, neuronal electrical activity is mapped to the representative pattern. This re-mapping process can be realized by nearest neighbor algorithm. Novel situation is considered to evoke novel activity pattern. Therefore, novel category for the novel situation should be autonomously generated (Figure 4). In addition, the novel category should be located near the category corresponding to similar situation in feature space. In this study, we implemented above strategy with dynamic category, using self-organization map (SOM). Spatiotemporal patterns of neuronal activity corresponding to the novel situations are expected to be mapped to nodes in the output layer, according to the similarity between the novel patterns and existent patterns. Seeding procedure (see section 2.2) links spatiotemporal patterns of neuronal activity to adequate purposive behavior. SOM also can be tuned by non-stop and non-teacher learning, which is useful for the system to follow the changes of activity pattern in neuronal network.

2.2 Design of SOM

In order to apply SOM algorithm to spatiotemporal pattern of electrical activity, the temporal snapshot of spike pattern is translated to a feature vector. Spikes above adequate threshold are counted within defined time window. In this study, the width of the time window is empirically defined, as 100 ms. Electrical activity patterns within a certain time window constitute a feature vector of 64 spike numbers detected at each electrode. Therefore, feature vectors corresponding to the temporal snapshots of spike pattern are continuously generated (Figure 5). Basic SOM-algorithm is employed for decoding neuronal electrical activity. In our case, two-dimensional output layer with 10 x 10 nodes arranged in lattice is provided in SOM. Each output node has a

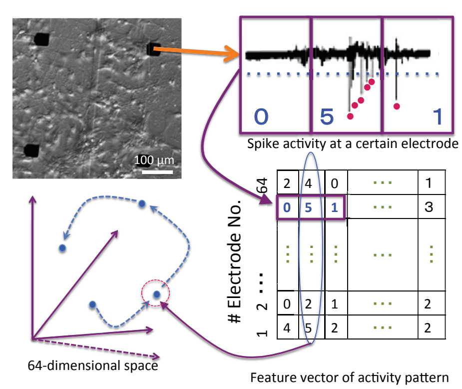

Figure 5. Generation of feature vector.

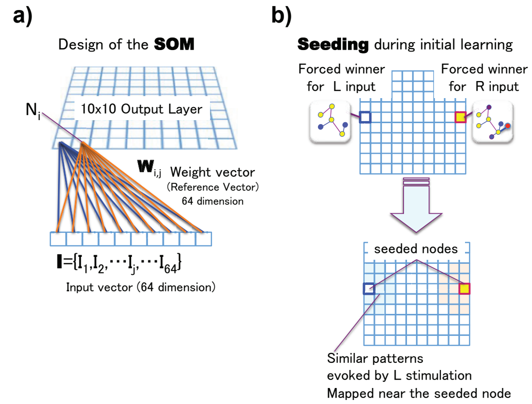

Figure 6. Design of SOM.

specific topological position in the output layer and is fully connected to 64 nodes of input layer, corresponding to each component of feature vector. The connections between an output node and input nodes are assigned to certain weights. In other words, each output nodes has a weight vector (reference vector) against input vector (Figure 6a). The SOM performs dimensional reduction of the feature vector, mapping a 64-dimentional feature vector to the specific two-dimensional output node. The node with the shortest Euclidean distance between an input feature vector and a corresponding reference vector is designated the winner for the input vector. The reference vector of the winner is then updated to more closely match the input vector. Simultaneously, the reference vectors of the neighboring nodes of the winner node are updated toward the input vector. This procedure places nodes corresponding to the similar spike patterns within neighborhoods. As a result of that, spatial relationships between the output nodes correspond to the relationships between the input vectors coupled to those nodes. These steps are implemented in an orthodox SOM algorithm. Winner node corresponding to a certain activity pattern should be coupled to the specific behavior adequate to the activity pattern. Therefore, winner nodes for the certain behavior should be gathered and should be anchored to the specific location. Therefore, SOM is initially trained by semi-supervised learning (Figure 6b). During the initial learning, the stimulation corresponding to the specific situations, assume obstacle near the left side of the robot body (L input) or obstacle near the right side of the robot body (R input), is repeatedly applied to LNC. The specific stimulations are achieved by changing the stimulation electrode according to the location of the IR sensor of the robot body with high value. Precise about the input procedure was described in previous papers [8-10]. At the same time, the specific

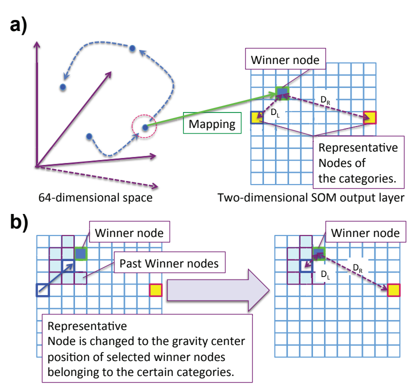

Figure 7. Generation of robot behavior.

node selected for each situation (L or R) is forced as the winner and reference vectors of the neighboring nodes are updated. We defined the procedure as "seeding" and the forced nodes as seeded nodes. By this procedure, similar patterns evoked by L or R stimulation are mapped near the seeded nodes (Figure 6b).

2.3 Generation of robot behavior depending on the location of the winner node.

The seeded nodes represent categories after seeding process. Therefore, Euclidean distances between the winner node and representative seeded nodes indicate the similarity of the winner node and certain categories (L or R, Figure 7a). If the distance between the winner node and representative node for L input is smaller than that for R input, speed of an actuator on right side is set to minus value, while speed of an actuator on contralateral side is set to plus value. The absolute value of the motor speed is decided by the ratio of distant between winner node and representative node for L and R.

2.4 Redefinition of representative nodes

The response of LNC gradually changes with development during culture days. Thus, fine-tuning of output is required to preserve adequate connection between LNC and a body. Representative nodes are initially seeded nodes and they are reselected depending on the spatial distribution of the successive winner nodes. Representative node is changed to the gravity center position of successive selected winner nodes belonging to the certain categories (Figure 7b). This process also guarantees that novel category corresponding to the novel situation is taken into the initial category, L input or R input.

3. Evaluation Experiment

We made Vitroid with SOM run within the field with two walls arranged in parallel. The distance between walls was 150 mm and longitudinal length of the field was 1200 mm (Figure 8a). All the procedure of animal experiments was conducted according to "Kwansei Gakuin University animal experiment administrative rules". Methods for preparing a dissociated culture have been described in previous papers [8,10,11]. Ages of LNC were from 20 to 60 days in vitro and embryonic day 18. All experiments were performed at room temperature. Embedded rule is the collision avoidance as described in previous sections. Seeding was performed 40 times for both of L input and R input in advance of the evaluation run. The basic robot speed is set to low, for avoiding delay of the response to the input signal.

4. Results and Discussion

SOM-Vitroid succeeded in collision avoidance running within a

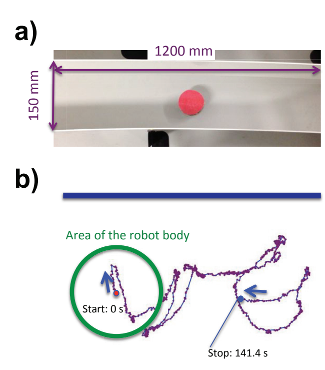

Figure 8. a) experimental environment.
b) Example of trajectory of the robot behavior

narrow space in all of 7 experiments (Figure 8b). Without inputs (corresponding that there are no obstacles near the robot body), SOM-Vitroid moved according to the spatiotemporal pattern of the spontaneous activity (SPT) in LNC. SPT is autonomous electrical activity evoked by synaptic transmissions without any inputs from outer world. Generally, this autonomous activity is frequently observed in a cultured neuronal network. The spatial distribution of winner node for L input and R input was separated each other in the output layer of SOM (Figure 9). Almost all the winner nodes for both of L input and R input gathered near each seeded node, however, there were a few winners positioned near the majority nodes for another category (Figure 9). There were repeatedly selected winners, suggesting the similar spatiotemporal patterns of neuronal activity were retrieved by the specific input. The mean selected numbers during experiments were 3.2±0.80 (mean±SE, N=5 experiments) for L input and 3.4±0.20 (mean±SE, N=7 experiments) for R input. The maximum rate of selection as a winner was 11 times in 16 selections, indicating success in seeding process. This pattern distinction highly depended on the feature of spontaneous activity in LNC. Response of LNC to external input was not always stable but was influenced by spontaneous activity. If input for a certain category is inputted for long time, the output of LNC was tend to be correct (Figure 10, b), while LNC cannot follow the input and spontaneous activity was dominant (Figure 10, a), in the case that the input was chattering between the two categories. Spontaneous activity was classified to L input or R input, according to the similarity between the feature vector of spontaneous activity and each feature vector for the specific category (Figure 10, c). We consider that this fluctuation caused by spontaneous activity contributes to generation of autonomous behavior and flexible behavior of the living animals.

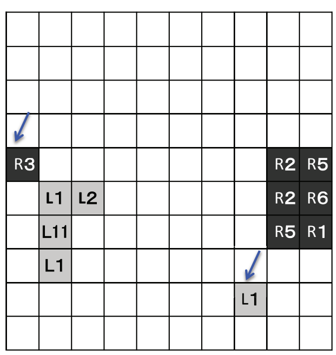

Figure 9. The spatial distribution of winner node for L input and R input. Arrows indicated winners positioned near the majority nodes for another category.

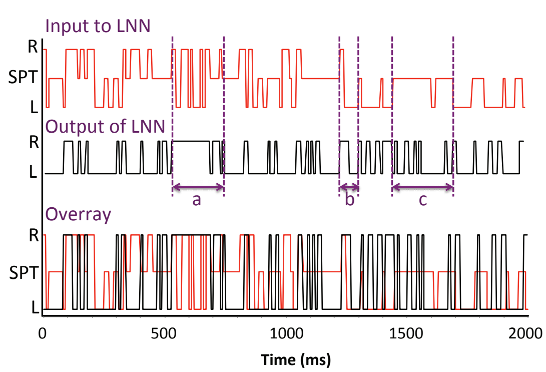

Figure 10. Trends of Input / Output to LNC.

5. Conclusion

We developed the neuro-robot system with a circuit of living neurons and outer world interfaced by a miniature-moving robot. As a representative example, we implemented SOM based algorithm to generate robot behavior. The winner nodes of SOM were gathered near the representative node for defined categories by initial semi-supervised learning process, and after that the mapping between inputted data and corresponding representative position in the clustering space was correctly updated by the robot behavior. In addition, SOM-Vitroid succeeded in generation of animal like flexible collision avoidance behavior.

6. ACKNOWLEDGMENTS

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