Analysis of causality network from interactions between nonlinear oscillator networks and musculoskeletal system

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Introduction

In order to understand the interactions between the body, brain and environment that generate various behaviours, it is necessary to consider the network structure that dynamically emerges from interactions among the brain regions even though the brain has a fixed anatomical structure (Bullmore and Sporns, 2009). Kuniyoshi and Suzuki (2004) proposed a model in which adaptive behaviours emerge through body constraints as chaotic itinerancy that is induced by coupled chaotic elements. Moreover, Yamada and Kuniyoshi (2012) revealed the influence of embodiment in nervous system by embodied network. They constructed an embodied network using transfer entropy based on motor information and found that the embodied network had the properties of a complex network. However, they did not specify the structures of the network and dynamic changes in the network structure caused by different movements.

In this paper, we address the network structure relationship that dynamically emerges through interactions between the network, body and environment. We conducted a physical simulation using a snake-like robot with a nonlinear oscillator network (Mori et al., 2013) and estimated the network structure based on transfer entropy for each different movement. We defined a wired network for the physically embedded network and a causality network for the estimated network structure. In order to understand the relationships of the oscillators in the emergent casualty networks within the periodic behaviours by the robot, we extract the causality subnetworks by Infinite Relational Model (IRM) (Kemp et al., 2006) and analyze the networks by the complex network theory. Moreover, we measured average transfer entropy between body and network to know relationship between body and the causality networks.

Experiment and Results

We conducted a physical simulation with a network structure as shown in Figure 1. The network consisted of Bonhoedeff-van der Pol oscillator for output neurons and hidden neurons that directly and indirectly connect with muscles in the robot, respectively.

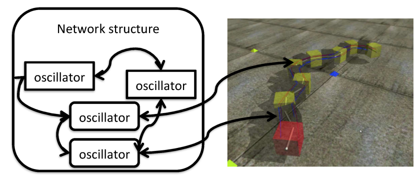

Figure 1: Model of snake-liked robot

$$\tau\frac{dx}{dt} = c(x - \frac{1}{3}x^3 - y + z) + \delta(S_f - x) \quad (1)$$

$$\tau\frac{dy}{dt} = \frac{1}{c}(x - by + a) + \epsilon S_f \quad (2)$$

$$S_f = \begin{cases} \alpha I + (1-\alpha)\frac{1}{K}\sum_{j=1,j\neq i}^{N} w_{ji}x_j & \text{if output neuron} \\ \frac{1}{K}\sum_{j=1,j\neq i}^{N} w_{ji}x_j & \text{else} \end{cases} \quad (3)$$

The oscillator neurons were updated according to Eqs.1 and 2. Each neuron was connected through binary-weighted connection of w, K is number of connections for each neuron. In these equations, a, b, and c control the neuron behaviour, z is a tonic input and δ and ϵ control the strength of the connections among the neurons. Moreover, α controls the strength of the ratio between the body and network, and I is the muscle length. In this research, we used $a = 0.7$, $b = 0.58$, $c = 2.0$, $\delta = 0.01$, $\epsilon = 0.01$, $\alpha = 0.5$ and $z = 0.3$. The network included 26 output neurons and 174 hidden neurons.

In order to distinguish different movements, Mean-shift clustering (Comaniciu and Meer, 2002) was used on a feature vector. The feature vector is constructed by correlation coefficient of between joint angles within a time window and dimensionally reduced by principal component analysis.

A causality network was constructed by means of transfer entropy (Schreiber, 2000) among the neurons for each longest movement pattern. The kernel estimation method was used to calculate the transfer entropy. Since transfer entropy has a direction, mutual information with IRM was used to estimate cluster and relationship in the causality network, here we defined each cluster as a subnetwork. The hyperparameters β and γ in (Kemp et al., 2006) were set 1 and

7. Figure 2 shows the topology of the wired network and the estimated relationships and clusters of the causality network according to the IRM with mutual information for the first and second longest movement pattern. As shown in Figure 2, causality networks when first longest movement pattern has less interaction with a subnetwork that has a many output neurons to another subnetwork.

In order to quantitatively measure interaction between body and network, average of transfer entropy was measured. As shown in Figure 3, low values of transfer entropy between hidden neurons and output neurons are observed during longer stable periodic movement.

To investigate the global property of the causality networks, average of clustering coefficient and shortest path length were calculated for each movement pattern. Figure 4 shows longer stable periodic movement when the causality network has a small clustering coefficient and large shortest path length that indicate the network has less complex network property.

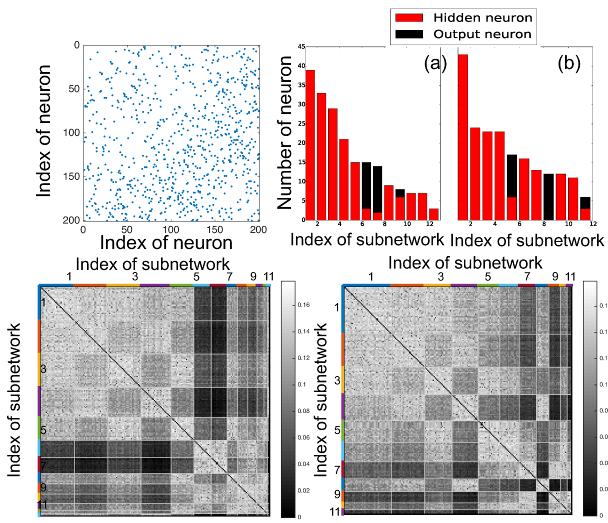

Figure 2: (top left) Topology of the wired network. (bottom left) Causality network for first longest movement pattern and (bottom right) second longest movement pattern are estimated by transfer entropy and clustered by IRM with mutual information. Colored bars on matrix indicate different subnetworks, and connections between different colored bars indicate interactions between subnetworks. (top right) Number of neurons including subnetworks for (a) first movement pattern and (b) second movement pattern.

Discussion and Conclusion

The presented results show that causality networks without complex network property and fewer interactions with subnetworks that had more output neurons to other subnetworks induced longer periodic movements. Therefore, periodic movement was dominated by the embodied network, and communication among the subnetworks induced exploratory movements.

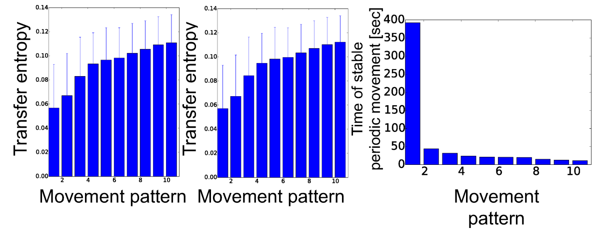

Figure 3: Average of transfer entropy (left) from hidden neurons to output neurons and (middle) from output neurons to hidden neurons. (right) Time of stable periodic movement for each longest movement pattern.

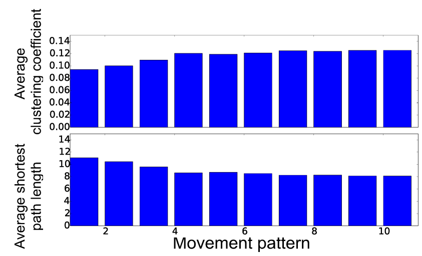

Figure 4: (top) Average clustering coefficient and (bottom) average shortest path length.

Many issues require further study, especially the interactions with different body structure and wired network. The network structure also needs to be analysed by other property of complex network.

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