Acquiring Body Representation for Reinforcement Learning Based on Slow Feature Analysis

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Abstract—The center of spatio-temporal representation for own body and its surrounding space is supposed at the parietal cortex in human brains, but the mechanism how the brain computes them is still not clearly understood though its hierarchical representation is expected. One of such hierarchical models, this paper propose a method which integrates multimodal information based on the Slow Feature Analysis (SFA) that enables sensory data abstraction in one modality and integration of abstracted multi-modal sensory information. To verify the proposed method, the reinforcement learning of reaching behavior is applied where the acquired representation from the visual and somatosensory information of arm movements of a robot is utilised as state space representation. The simulation result shows that multimodal information related to self movement is transformed into lower dimensional data that changes slowly, which is useful for reinforcement learning to improve its performance.

Keywords—Slow Feature Analysis, Multimodal, Body Representation, Reinforcement Learning

1 Introduction

How to represent the own body and its surrounding space is one of the essential issues for humans and also robots to perform various kinds of tasks. The parietal cortex in human brain is supposed to be the center of such representation in a hierarchical manner. However, the detailed mechanism how the brain computes such representation is still not clearly understood. Constructive approaches to the issue by integrating multimodal sensory data have attacked in cognitive developmental robotics (for a survey, [1]), and among them, Fuke et al. [2] proposed a method of acquiring visuo-tactile or visuo-spatial representation. In this model, the same posture (joint angle of the arm) is used for extracting invariance from visual information. Nishikawa et al. [3] proposed a method of state space construction with time transition of input signal. They integrated multimodal information of humanoid robot such as visual, somatosensory, and tactile ones in a hierarchical model using Slow Feature Analysis (SFA) [4] and showed that SFA network could construct better state representation for reinforcement learning than using raw sensor data. However, while they indicated that SFA was beneficial for representation of the own relative position to the environment, it is not clear that their model is applicable to body representation. In this paper, we deal with arm movement and show that SFA network constructs useful representation for reinforcement learning related to body movement and space around the arm by integration of multimodal information.

2 Slow Feature Analysis Network

Slow Feature Analysis (SFA) is an unsupervised learning algorithm for extracting slowly varying features from a quickly varying input signal. The SFA algorithm solves the following optimization problem: Given an N-dimensional input signal $\boldsymbol{x}(t) = [x_1(t), \ldots, x_N(t)]^T$, find a set of J input-output functions $g_j(\boldsymbol{x})$ such that the output signals

$$y_j(t) = g_j(\boldsymbol{x}(t)) = \boldsymbol{w}_j^T \boldsymbol{x} \tag{1}$$

minimizes

$$\Delta(y_j) := \langle \dot{y_j}^2 \rangle_t \tag{2}$$

under the constraints

$$\begin{aligned} \langle y_j \rangle_t &= 0 \quad \text{(zero mean)} && (3)\\ \langle y_j^2 \rangle_t &= 1 \quad \text{(unit variance)} && (4)\\ \forall\, i < j,\ \langle y_i y_j \rangle_t &= 0 \quad \text{(decorrelation)} && (5) \end{aligned}$$

where $\boldsymbol{w}_j$ is a weight vector. Figure 1 shows the hierarchical SFA network model that integrates visual and somatosenrsory (joint angle) information.

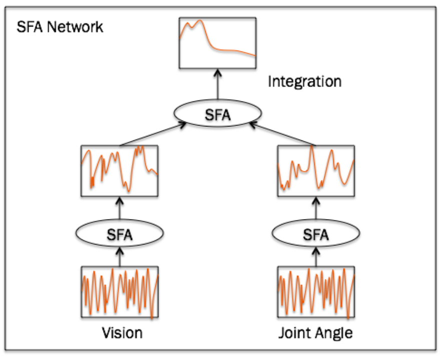
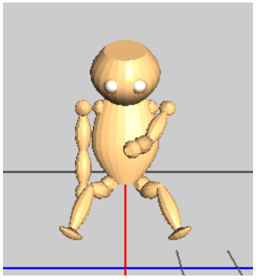


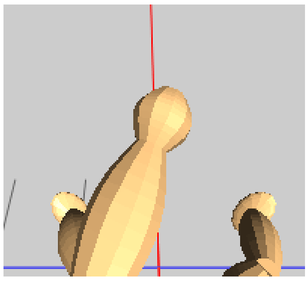
Figure 1: Hierarchical integration model of multimodal information

3 Simulation Experiment

To validate the model, we carry out a simulation with a dynamics simulator that has arms with 5 degrees of freedom and a vision system as shown in Figure 2.



(a) The robot appearance

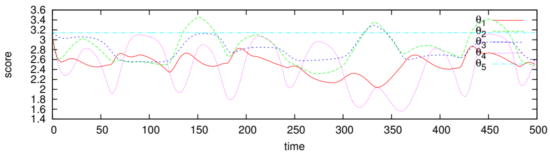


(b) A robot view

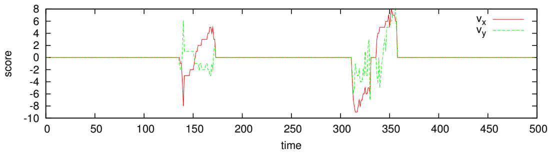
Figure 2: The simulation robot

3.1 Slow Feature Extraction

We apply SFA in a similar hierarchical manner to the raw sensor data that are shown in Figure 3 for both modalities (i.e. 5 joint angles and 49 two-dimensional optical flow vectors, where we segment the image into 7×7 pixels) when the robot moves its arm randomly for 500 time-steps. Then, slow features extracted in each modal information are integrated to more global and abstract features.



(a) Joint angle



(b) Optical flow (x, y component of one pixel)

Figure 3: Raw data

The result is shown in Figure 4. The fastly and locally changing signal of the input is transformed into slow features which are smoothly changing on the whole.

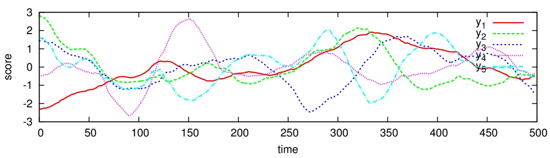


Figure 4: Extracted slow feature

3.2 Reinforcement Learning

To evaluate the acquired representation, we apply reinforcement learning of reaching behavior with the extracted features through the SFA network. Joint torques of the arm were designed a priori. We construct a neural network which connects from the most slow 15 outputs of SFA network to the state value function. Positive reward (+1) is given when the hand reaches a certain position in front of the face and 0 reward else. The robot updates the state value function of which TD is applied for the learning. The result that the state value of learning phase is shown in Figure 5. The learned state value becomes higher as the hand approaches to the goal.

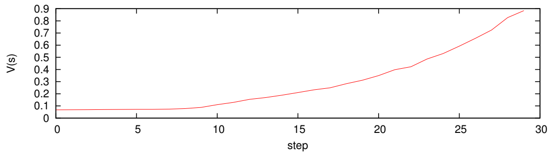


Figure 5: Learned state value

Next, we conduct an evaluation phase: The robot moves its arm from the slightly different start positions to the same goal position. In this case, the goal is the same but the trajectory is not the same. The result of the state value estimation of evaluation phase is shown in Figure 6. The red curve with using SFA output becomes higher as the hand approaches to the goal position, while with using raw data shown as the green curve, state value is not well estimated.

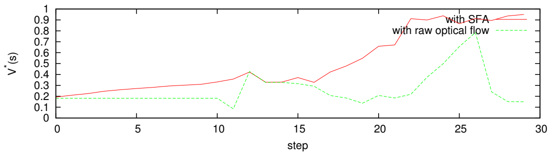


Figure 6: Estimated state value

4 Conclusion

In this study, we have shown that hierarchical SFA network transforms multimodal information into some lower dimensional data that changes slowly, which is useful reprensentation for reinforcement learning. In many tasks, slowly varying features such as body movement and position are important. Future work will include generalization of integrated representation with data in comparison with various kinds of coordinate systems in parietal cortex, and we will verify practical effectiveness of motor learning.

References

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