Title	Autonomous Learning Based on Depth Perception and Behavior Generation
Author(s)	Jeong, Sungmoon; Park, Yunjung; Lee, Minho
Citation	2013 IEEE Third Joint International Conference on Development and Learning and Epigenetic Robotics (ICDL): 1-2
Issue Date	2013-08-18
Type	Conference Paper
Text version	author
URL	http://hdl.handle.net/10119/11608
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Description	

Autonomous Learning Based on Depth Perception and Behavior Generation

Sungmoon Jeong[1,3], Yunjung Park[2] and Minho Lee[1*]
[1]School of Electronics Engineering, Kyungpook National University, 1370 Sankyuk-Dong, Puk-Gu, Taegu 702-701, Korea
[2]School of Robot Engineering, Kyungpook National University, 1370 Sankyuk-Dong, Puk-Gu, Taegu 702-701, Korea
[3]School of Information Science, Japan Advanced Institute of Science and Technology, 1-1 Asahidai, Nomi, Ishikawa 932-1292, Japan
*mholee@knu.ac.kr

***Abstract*— We propose a new neuro-robotic network that can achieve a goal oriented behavior for a visually-guided object manipulation tasks based on learning by examples. The proposed model considers a brain-like interaction between behavior generation and depth perception in mammal brain to autonomously improve the robot's action performance and perception accuracy. The brain exploits action to develop perception qualities, and this updated perceptual process helps to develop qualified-behavior. The perceptual accuracy can be enhanced by observing the effects of actions that preserve a physical and/or perceptual invariance. Also, the improved perceptual accuracy can influence the optimal selection and/or modification of actions. In order to import those action and perception abilities of a brain into a humanoid robot, we considered two key inspirations: 1) Sensory Invariant Driven Action (SIDA) and 2) Object Size Invariance (OSI) in depth perception. Considering robot manipulation of a target object with distance estimation as a perceptual process, we develop a new autonomous learning method based on the SIDA for behavior generation and OSI property for perceptual judgment. The proposed method is evaluated by using a humanoid robot (NAO) with stereo cameras, and the experimental results show that the proposed method is effective on autonomously improving the behavior generation performance as well as depth perception accuracy.**

Keywords—component; Autonomous learning, sensory invariance driven action, size invariance of object perception

I. INTRODUCTION

How does the brain learn to transform sensory data into accurate perceptual information while, at the same time, learning to solve complex behavioral tasks? The brain exploits action to develop perception qualities and this updated perceptual process helps to develop qualified-behavior. Poor quality of the perceptual information, due to incomplete development and/or training, can interfere with learning to solve behavioral tasks, while actions can influence perceptual judgments. Perception and action are deeply related, and each of them can be used for improve the performance in the other side. What an agent can see depends on where it directs its sensors, and what an agent senses often determines which course of action the agent will take. For example, behavior generation task to manipulate an object requires an embodied agent to estimate the distance from the agent's body to a target object through vision. How can an agent learn to make sense of these sensory signals to accurately estimate the distance to the target object while, at the same time, an agent learns to make a policy to manipulate the target signal? If we hope to implement an intelligent artificial agent that can emulate the autonomous learning abilities of human to solve complex problems in the physical world, then the developmental learning mechanism based on action and perception will be a key issue to implement such a smart artificial agent.

However, due to the complexity of the problem, previous literatures have focused on the study of action or perception in isolation. Those attempts to modularize the problems seemed natural because we often spoke about perception and action as if they were two different processes. Recent neuro-scientific research, on the other hand, has provided strong evidence that perception and action are not isolated processes [1-4]. Those processes interact with one another, often in complex ways.

This work attempts to understand how humans and animals might solve a fundamental problem: How does the brain learn to transform sensory data into accurate perceptual information while, at the same time learning to solve complex behavioral tasks? This is a puzzling problem because humans and animals are not born with the ability to transform raw sensory data into perceptual information to solve various problems throughout life. We assumed that there is one option to solve this problem: they can try to first solve the sensory problem by using action ability and only after that problem is solved, they can focus on solving the behavioral problem by using updated perception ability. To investigate this problem, we implemented this option on a humanoid robot faced with the task of interacting with physically distant object. Because the task requires understanding physical spaces, the robot needs to learn to transform binocular visual images of a target object into accurate depth estimates. The estimated depth perception affects to modify and/or select optimal behavior generation of the robot to achieve the desired manipulation task.

To evaluate the learned depth estimator, we applied it to the problem of depth prediction at various distances with specific behavior generation task in same time. We also recorded behavioral information during evaluation while considering with and without developmental learning mechanism, and compared these measures to determine whether one condition was superior to the other with respect to learned behavior. We found that the proposed developmental learning mechanism

This research was partly supported by the Original Technology Research Program for Brain Science through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology (2012-0005794) (50%) and this research was partly supported by the Industrial Strategic Technology Development Program(10044009, Development of a self-improving bidirectional sustainable HRI technology for 95% of successful responses with understanding user's complex emotion and transactional intent through continuous interactions) funded by the Ministry of Knowledge Economy(MKE, Korea)" (50%).

produced higher qualified binocular distance estimates and resulted in higher quality of behavior on an object manipulation task.

II. BACKGROUND

Previous research has primarily focused on either learning to perform some behavioral task for robot with fixed perceptual processing or learning to improve perceptual processing either passively (without action) or actively. In the next two subsections we will describe the approaches that have been applied to construct autonomous learning mechanism for action and perception.

A. Sensory Invariance Driven Action (SIDA)

A key inspiration for our approach is the idea of Sensory Invariance Driven Action (SIDA) [5]. SIDA explains how the brain can learn the meaning of encoded sensory stimuli. Because the brain does not have direct access to external stimuli, a critical problem facing the brain is to understand the meaning of complex neural spiking patterns and to use those patterns to make decisions about how to act in the world. The critical insight of SIDA concept is that "learn to act in a way which maintains invariance in internal sensory representations", is a useful mechanism for learning the meaning of encoded sensory stimuli. SIDA concept emphasizes the role of simultaneously learning about both sensory information and action.

The notion of SIDA is similar to the idea of intrinsic motivation because both SIDA and the idea of intrinsic motivation propose a mechanism for learning about the agent-environment interface without respect to a particular goal. Both ideas direct the agent to learn general knowledge about the environment. However, SIDA emphasize she role of simultaneously learning about both sensory information and action, which is more closely related to our current objective. In the next section, we train the robot to maintain perceptual invariance in situations where, although the robot has physically moved (in our case, by rotating its neck), its action should, in principle, not alter the true distance from robot to the target. If the robot's perceived distance estimate differs, then we can use this difference as an error signal for training by robot-self.

1) Distance invariance

Based on stereo cameras, we can easily obtain distance by using the radians of two angles (θ_R; θ_L) of the center of target object (x; y) in two cameras by simple triangular equation with focal length and CCD width of two cameras [10]. However, notice that the left and right angles estimate depend on the robot's ability to accurately detect the center of the target object location from the left and right camera images. If these x-coordinates are biased, then they introduce bias into the angle estimates. Therefore, very small biases to$\theta_R$and θ_L can cause large errors in distance estimates as the distance of the target from the observer grows.

One way to improve the ability of distance estimation by vision sense is to acquire several training samples that, in principle, should have identical distance from the agent to remove the biases to θ_R and θ_L. As long as every sample has identical distance from the observer, the agent can invent a distance unit and apply that to all of the samples. Using these samples would allow us to eliminate biases that produce inconsistent distance estimators [6]. In order to find appropriate parameter values, we have applied genetic algorithms in [6].

Now if we have a strong enough parametric model, we can generalize to other distances. The main question is: How can the agent acquire samples that should, in principle, have identical distance from the observer? The use of head movements such as rotation and shifting for depth estimation is strongly supported by observations of birds, small mammals, and insects [7], [8]. It has also been established that humans use head motion for depth perception [9]. Head movement does not require high level cognitive abilities and does not depend on binocular depth estimation. Thus we may be able to use head movement to train binocular depth estimation. Note that when a humanoid robot rotates its neck, the axis of rotation remains invariant, with respect to distance, to points that were not rotated. So if the robot rotates its neck, the distance from the neck to the target point remains invariant, even though the distance from the cameras to the target may have changed as shown in Fig. 1. Now, if the agent estimates distance from the axis of neck rotation to the target, it can easily acquire samples that should, in principle, have identical distance to the origin. This physical invariance can expose perceptual inconsistency, which can be used to train a perceptual process [6].

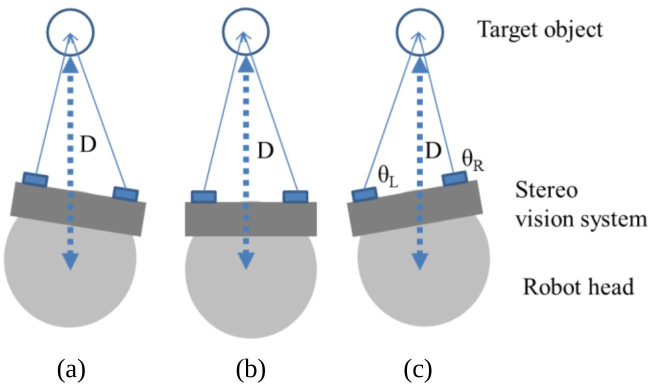


Fig. 1. If the origin is the axis of neck rotation, then rotating the neck does not change the distance to the target, even though the distance from the left and right cameras may have changed.D: distance from robot to target object, θ_R, θ_L: angles of the center of target object at right and left cameras.

Because an agent does not have a complete model of its environment, it needs to explore the effects of various actions to determine their long-term value. Once the agent estimates of the value of each action, the agent can exploit this knowledge to behave intelligently. However, the agent has to decide when to stop exploring and start exploiting. If the agent stops exploring too early, the estimated value for each action may be inaccurate. On the other hand, if the agent explores for too long, then it potentially wastes resources on exploring. This problem is known as the exploration-exploitation dilemma. Thus, it is important to decide the suitable timing for the specific action such as head movements to gather training data by considering distance invariance.

B. Size invariance

Focusing on manipulation of a target object with distance estimation as the perceptual process by bimanual motor action, the agent should decide when to approach the target object by walking or rotating and should manipulate the target object within suitable distance and angle between agent and target object. It means that the agent should understand a suitable timing for policy of action and physical relationship between the agent and target object in same time.

Fig. 2 shows the comparison of perceived object size according to different distance. Given that a physical object typically maintains the same size (i.e. it is size invariant), we may be able to use this physical invariance to learn about physical relationship between the agent and target object. However, it is important to keep in mind that the size itself is not, in general, a reliable clue of distance unless we know the size of the object at a reference distance. This information can be used as a training set for our binocular vision system. Unfortunately the relationship between perceived size and distance is not linear [6]. But there is a straight forward relationship between size and distance. We use a relationship between distance and perceived size modified from [11]:

$$D = \frac{(D_0 \times s_0)}{s} + \alpha \tag{1}$$

where D is the distance given the current observation, s is perceived size of the object given the current observation, $D_0$is the reference distance of the object for which the perceived size is known, s_0 is the perceived size of the object at reference distance $D_0$and α is a constant. Using Eq. (1), we can establish a linear relationship for training our binocular vision system. Therefore, size invariance could be useful value as a reference to update poor qualified depth parameters. Also, it could be used to decide when the robot should update depth parameters by gathering training data. Moreover, as a result of accurate distance estimator, the agent could generate suitable actions for achieving behavior task by considering accurate distance estimation.

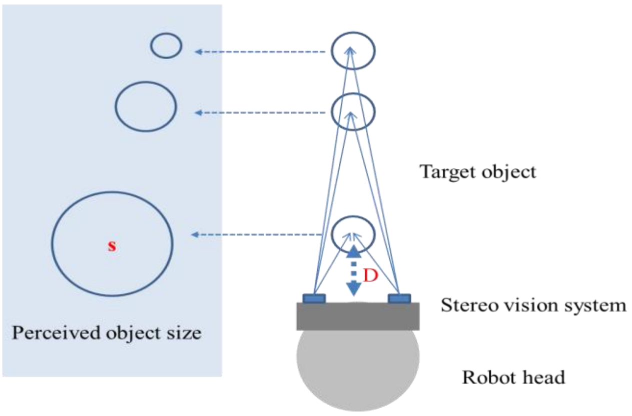


Fig. 2. Comparison of perceived object size according to different distances

C. *Manager for selction of action and perception*

Based on the object size invariance (OSI) characteristic, robot can enhance the depth perception ability. After that, simple reinforcement learner can easily decide the suitable action to achieve the goal directed behavior task with object according to a result of perception. In order to autonomously decide the suitable action, we pre-define a reinforcement learning strategy for understanding the spatial relationship between robot body and target object. We consider three different states considering both the quality of perception ability to estimate physical distance which is measured by the OSI and spatial relationship such as distance and angle points of view as shown in Table I. The reinforcement learning generates a suitable behavior patterns corresponding to three different states both for perception ability and spatial relationship.

TABLE I. Q-TABLE FOR PROPOSED MODEL

States	***Reinforcement learner***
State 1	Object is not located in center position of robot body
Action 1	Rotating to the target object
State 2	Object is not located in appropriate distance from robot
Action 2	Walking to forward or backward side from target object
State 3	Object is located in appropriate position from robot
Action 3	Big turning to righ-side

III. PROPOSED AUTONOMOUS LEARNING MECHANISM

A. *Experimental setting*

Our experiments were implemented on an Aldebaran NAO humanoid robot with two cameras mounted on its head that were used for binocular depth estimation as shown in Fig. 3. Nao is a bipedal humanoid robot with existing software modules that enable the robot to behave. Movement of the arms, neck, and head are controlled by manipulating joint angles. This platform allows us to investigate binocular depth estimation as well as behavioral object manipulation tasks that require locomotion.

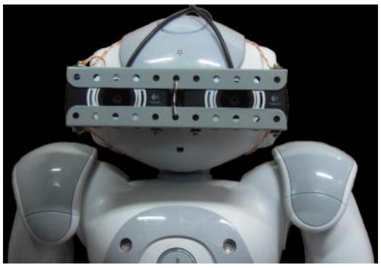


Fig. 3. Nao humanoid robot platform with stero cameras

One cardboard tower is located in similar height (52cm from floor) at the same level as the robot's eye. The position of the color mark was fixed and the NAO's initial position as shown in Fig.4. The two stereo cameras, each having a resolution of 640x480 and 60°field of view, are separated by 76mm. Goal directed behavior task was defined that humanoid robot should understand current states of physical body and target object, and then approach the target object to hit it on appropriate distance from the target object. In order to do so, robot should have qualified depth estimation (perception) ability and should understand about the relationship between action and perception according to a (given) physical environment. In the current experiment, the robot was trained about the relationship between object size and physical distance by considering the OSI characteristic. Based on the OSI characteristic, this relationship is used as reference depth-perception result to correct parameters for estimating more accurate depth information. Also, according to enhanced depth perception ability, humanoid robot could autonomously generate suitable behavior to hit the target object. Therefore, perception (depth estimation) can guide appropriate action which can help to understand about environment at the same time. The basic actions such as head rotation to update depth parameter, approaching, finding, and hitting to the target object are previously trained by Multiple Timescales Recurrent Neural Networks (MTRNN) [12]. After training the basic behavior sequences, the tests were conducted for achievement of goal-directed behavior generation by using trained basic behavior with suitable timing. It was considered that a trial was successful if the target object was successfully knocked down by the robot arm during the course of the experiment.

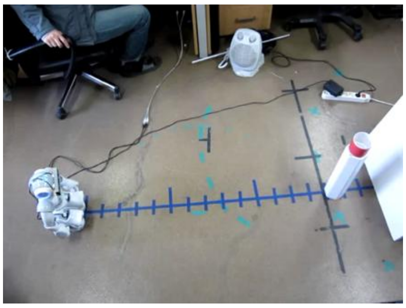
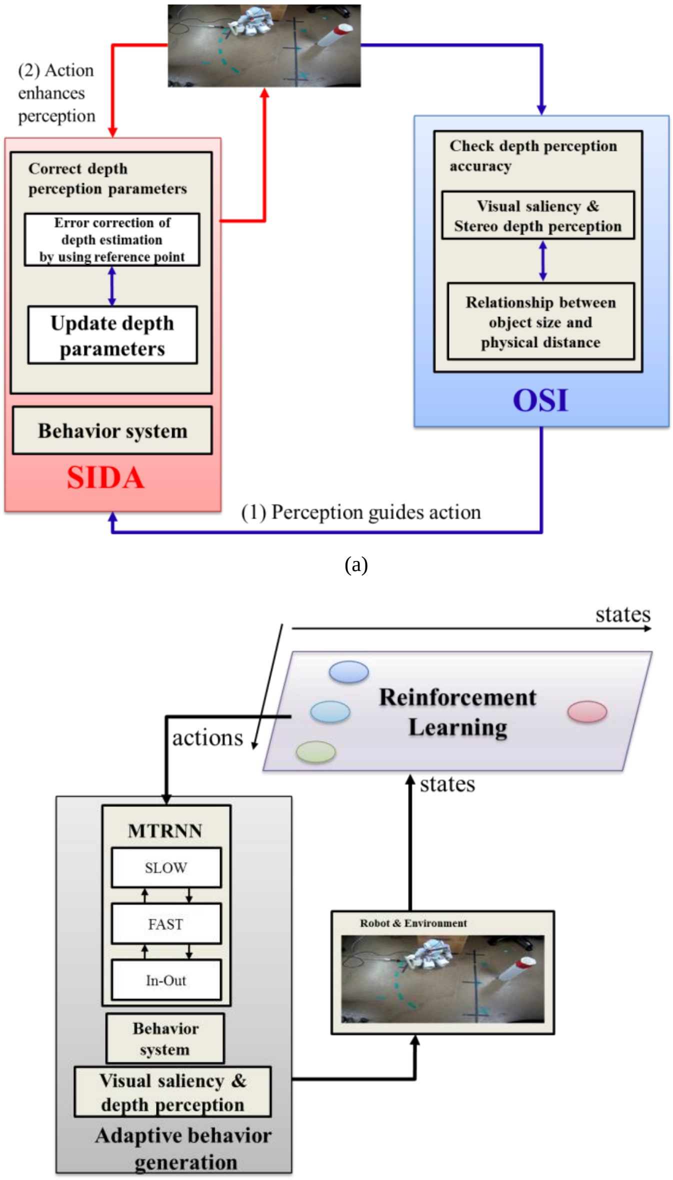


Fig. 4. Experimental workbench

B. *Overall architecture*

The proposed model consists of two main parts; (1) OSI and SIDA based autonomous learning model to enhance action and perception abilities in same time and (2) adaptive behavior sequence generation to achieve the tasks involving target object by using MTRNN, reinforcement learner and updated depth perception ability. Figs.5 (a) and (b) describe the block diagram of proposed model to enhance depth perception ability and adaptive behavior generation model. The two main parts have different roles and work in shifts throughout the running time. First, in Fig. 5 (a), OSI decides suitable timing to correct the current depth parameters for getting accurate depth estimation, and updating of the depth parameter is working based on SIDA if the current depth accuracy doesn't enough. After updating depth parameters, Fig. 5 (b) describes adaptive behavior sequence generation model which is to achieve the tasks involving target object by using MTRNN and reinforcement learners with the updated depth parameters.



(a)

(b)

Fig. 5. Block diagram of robot behavior generation model. (a) OSI and SIDA based autonomous learning model, (b) adaptive behavior generation model based on MTRNN and reinforcement learner with updated depth parameters

The selective visual saliency map in Figs. 5 (a) and (b) is used for sequentially pop-out the salient areas within the environment and estimate depth information of the salient area or object [10], [13].It is important to compare the estimated depth information with the size invariance characteristic to decide whether the current parameters for depth estimation are appropriate value according to the current robot states. Also, the selective attention model helps the robot to easily identify the target with in the environment.

The pre-trained behavior functions by MTRNN are used to control the robot and the reinforcement learner selects one of the pre-trained functions. The inputs for the reinforcement learner consist of spatial information related to a target object. The reinforcement learner predicts 3 different behavior commands (A_t: turning, walking, hitting) through time. The inputs for the MTRNN consist of visual attention command (v_t), robot behavior command (b_t) and spatial information (s_t). Here, the visual attention and behavior commands indicate one of the three different colored objects (red, green and blue) and one of the three different behavior categories (walk, turn and hit) respectively. Spatial information consists of 2 different relations (angle and distance) between the robot states and the target object. The visual attention and behavior commands are transformed by a Topology Preserving Map (TPM) to cluster as 16 TPM units and spatial information is transformed to 64 TPM units in our experiments [12]. The stereo visual attention system receives a visual attention command from the MTRNN and the retina image from the robot's vision [14]. The spatial location of a target object is encoded by using an angle between the robot body and a target object together with depth information obtained from the stereo-type visual attention system. The spatial location of a target object, the visual attention and behavior commands are fed back as inputs to the MTRNN.

C. Visual attention and depth estimation based on stereo vision system

In the course of detecting an object to achieve a desired object manipulation task, the stereo-type Saliency Map (SM) model works for selecting a specified object region in an input scene and estimates the depth for a specified object region [13]. It is important to recognize whether current states are similar with the initial state in which the bi-pad robot learns in advance, and also continuously catches the visual environment to generate the suitable behavior patterns by the MTRNN. A localized area selected by a bottom-up SM model is tested for matching how much the selected area meets the visual characteristics such as color of an object for a behavior sequence generation by the MTRNN. For example, if a visual attention command from the MTRNN is to find a blue object, then only the blue characteristic is intensified in the SM model and other colors are inhibited. After successfully localizing the corresponding landmarks on both the left and right images (θ_R, θ_L), the robot obtains depth information by means of the stereo visual attention model using simple triangular equation [10].

D. Adaptive behavior generation

Prior to the actual training of the MTRNN for the behavior sequence generation, reinforcement learning is used to adjust the initial state of the robot. After correcting the initial state of the robot, we considered adaptive behavior generator to achieve the goal-oriented multiple object manipulation task. The MTRNN is a type of Continuous Time Recurrent Neural Network (CTRNN) model in which neurons have different time scales; therefore, the MTRNN has the functional hierarchy characteristic [12]. Due to this characteristic, neurons with a fast time constant encode a set of primitive behaviors, and neurons with a slow time constant prepare for the compositional sequences of the primitive behavior. The MTRNN has three groups of neural units in present study, namely input-output units, fast context units and slow context units. The input units consist of visual input (angle and depth), visual attention command and behavior command. The 8 dimensional inputs were transformed into 68 dimensional sparsely encoded vectors by a TPM with 3×10^6 training epochs [12]. This transformation reduces the redundancy of the input trajectories for units. The fast context units are connected with the input-output units of which synaptic weights are determined through learning by examples. The membrane potential of these neurons is modeled by the conventional firing rate model which is calculated by linear differential equation.

The context units are connected with the input-output units of which synaptic weights are determined through learning by examples. The membrane potential of these neurons is modeled by the conventional firing rate model which is calculated by linear differential equation given by Eq. (2)

$$\tau_i (du_{i,t} / dt) = -u_{i,t} + \sum_j w_{ij} x_{j,t} \tag{2}$$

where $u_{i,t}$ is the membrane potential of each i-th neural unit at time step t and $x_{j,t}$ is the neural state of the j-th unit at time step t, and w_{ij} is a synaptic weight from the j-th unit to the i-th unit. The time constant τ is defined as the decay rate of a unit's membrane potential. If the τ value is large, the activation of the unit changes slowly because the internal state potential is strongly affected by the history of the unit's potential. On the other hand, if the τ value is small, the effect of history of the unit's potential is also small, and thus it is possible for activation of the unit to change quickly. The activity of the fast context units with small time constant ($\tau = 2$) changes quickly, whereas the activity of slow context unit with a large time constant ($\tau = 30$) changes slowly. The updating of $u_{i,t}$ values is done using Eq. (3), which is the numerical approximation of Eq. (2)

$$u_{i,t+1} = (1 - 1/\tau_i) u_{i,t} + (1/\tau_i)(\sum_{j \in N} w_{ij} x_{j,t}) \tag{3}$$

The activation of the i-th unit at time t is determined by the following Eq. (4) using non-linear activation function

$$y_{i,t} = \begin{cases} \dfrac{\exp(u_{i,t})}{\sum_{j \in Z} \exp(u_{j,t})} & if\ i \in Z \\ f(u_{i,t}) & otherwise \end{cases} \tag{4}$$

where Z is a set of output units that correspond to visual attention command or behavior command. The softmax activation function is applied only to the output units, and not to the context units. Activation values of the context units are calculated by the function f which is a conventional unipolar sigmoid function.

The MTRNN is trained to obtain the optimal connective weights by minimizing the learning error E. The error function E was defined by the Kullback-Leibler divergence, as shown in Eq. (5)

$$E = \sum_t \sum_{i \in O} y^*_{i,t} \log(y^*_{i,t} / y_{i,t}) \tag{5}$$

where $y^*_{i,t}$ is the desired activation value of the output neuron at time t, O is a set of output units, and $y_{i,t}$ is the activation value of the output neuron with the current connective weight. A conventional back propagation through time (BPTT) algorithm was used to train the model [14]. Through iterative calculation of the BPTT, the values of the connective weights reach their optimal values in the sense that the errors between a teaching sequence and an output sequence is minimized.

IV. EXPERIMENTAL RESULTS

The purpose of this experiment was to determine whether there is an advantage in updating the behavioral and perceptual processes as compared to without learning process. In order to show the advantage of depth parameter learning with SIDA concept, initial parameter values are randomly set. Robot generates specific action such as head movement to gather the training data by considering SIDA concept. It means that this specific action can enhance for perception skill [6]. Table II shows the results of reinforcement learning.

TABLE II. Q-TABLE FOR PROPOSED MODEL

States	**Actions**		
	Action 1	***Action 2***	***Action 3***
State 1	2.52166	0.0465623	0
State 2	2.66569	13.6363	2.96754
State 3	-0.188005	0.096173	-0.173884

Based on the Table II, robot autonomously generates suitable behavior considering estimated depth. Therefore, the estimated depth information is important to select appropriate behavior at each time step. Table III shows the comparison of depth estimation accuracy at each running step by considering with and without learning at initial running step using SIDA and OSI characteristic. As shown in Table II, learning with SIDA concept and OSI characteristic can enhance the perception ability to estimate the depth information as compared to estimation without learning based on SIDA and OSI characteristic. Also, this updated depth parameter can guide suitable behavior to achieve the goal-directed behavior task. For example, robot can effectively generate approach the target object within appropriate distance to hit the target object. However, poor depth parameters caused poor behavior such as getting closer than required to the target object. This poor behavior caused the robot to knock down the target object by its body or it missed the target object. Therefore, the robot could not complete the desired manipulation tasks.

TABLE III. ACCURACY OF PERCEPTION ABILITY TO ESTIMATE DEPTH

Robot steps	**Distance from robot to target object (mm)**		
	Ground truth	***Without learning***	***With learning***
1st	**1511.94**	2054.08	**1499.52**
5th	**706.88**	871.72	**735.02**
7th	**561.13**	700.29	**593.67**
9th	**481.68**	578.89	**505.99**

V. CONCLUSION

We proposed a new autonomous learning mechanism based on action and perception. There are two main contributions: (1) simple actions and low level visual processing can improve depth estimation, (2) maintaining that the perceptual invariance is a powerful principal for implementing the autonomous developmental robot. The experiments show that the proposed model can autonomously generate the behavior sequences to improve ability of action and depth estimation (perception).

As a future work, we would like to answer: (1) what other invariances can be used to calibrate perceptual predictions? (2) And how can we learn accurate parameters in more complex error situations? (3) What kinds of principles can iteratively and continuously improve the action and perception in a cyclic learning process?

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