

Optic Flow Based Skill Learning for a Humanoid to Trap, Approach to, and Pass a Ball

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Abstract. Generation of a sequence of behaviors is necessary for the RoboCup Humanoid league to realize not simply an individual robot performance but also cooperative ones between robots. A typical example task is passing a ball between two humanoids, and the issues are: (1) basic skill decomposition, (2) skill learning, and (3) planning to connect the learned skills. This paper presents three methods for basic skill learning (trapping, approaching to, and kicking a ball) based on optic flow information by which a robot obtains sensorimotor mapping to realize the desired skill, assuming that skill decomposition and planning are given in advance. First, optic flow information of the ball is used to predict the trapping point. Next, the flow information caused by the self-motion is classified into the representative vectors, each of which is connected to motor modules and their parameters. Finally, optical flow for the environment caused by kicking motion is used to predict the ball trajectory after kicking. The experimental results are shown and discussion is given with future issues.

1 Introduction

Recent progresses of humanoid robots such as ASIMO [3], QRIO [6], HOAP [8], and MORPH [2] have been attracting many people for their performances of human like behaviors. However, they are still limited to very few behaviors of individuals such as walking and so on. In order to extend the capability of humanoids, various kinds of behaviors with objects or other agents should be developed. RoboCup has been providing an excellent test-bed for such a task domain, that is, ball operation and cooperation with teammates (competition with opponents) [5]. Towards the final goal of RoboCup Soccer, the humanoid league has been held since 2002 in Fukuoka, and several technical challenges such as standing on one leg, walking, and PK have been attacked. However, the level of the performance is still far from the roadmap to the final goal [4]. Further, many teams developed humanoid behaviors based on the designers knowledge on the environment, and therefore seem to be brittle against the environmental

changes. It is expected that a robot obtains the environmental model through the interactions with its environment.

Optical flow has been used to learn the sensorimotor mapping for obstacle avoidance planned by the learned forward model [7] or by finding obstacles that show different flows from the environments using reinforcement learning [9]. In addition, it is used for object recognition by active touching [1]. In these studies, the number of DoFs is much fewer than humanoids; therefore, it seems difficult to apply their methods to realize various kinds of humanoid behaviors. Especially, generation of a sequence of behaviors is very hard but necessary for the RoboCup Humanoid league to show not simply an individual robot performance but also cooperative ones between two robots. In the latter case, the following issues should be considered:

1. decomposition into basic skills,
2. basic skill learning, and
3. switching the learned skills to generate a sequence of behaviors.

A typical example task is passing a ball between two humanoids (face-to-face pass). Since attacking all of these issues together is so difficult, we focus on the second issue, and present three methods for basic skill learning (trapping, approaching to, and kicking a ball) based on optic flow information by which a robot obtains sensorimotor mapping to realize the desired skill, assuming that skill decomposition and planning are given in advance. First, optic flow information of the ball is used to predict the trapping point. Next, the flow information caused by the self-motion is classified into the representative vectors, each of which is connected to motor modules and their parameters. Finally, optical flow for the environment caused by kicking motion is used to predict the ball trajectory after kicking. The experimental results are shown and discussion is given with future issues.

2 Task, Robot, and Environment

2.1 Robots Used

Fig. 1 shows biped robots used in the experiments, HOAP-1, HOAP-2, and their on-board views. HOAP-1 is 480 [mm] in height and about 6 [kg] in weight. It has a one-link torso, two four-link arms, and two six-link legs. The other robot, HOAP-2, is a successor of HOAP-1. It is 510 [mm] in height and about 7 [kg] in weight. It has two more joints in neck and one more joint at waist. Both robots have four force sensing registers (FSRs) in their foots to detect reaction force from the floor and a CCD camera with a fish-eye lens or semi-fish-eye lens.

These robots detect objects in the environments by colors. In this experiment, a ball is colored orange, and the knees of the opponent robot are colored yellow. The centers of these colored regions in the images are recorded as the detected position.

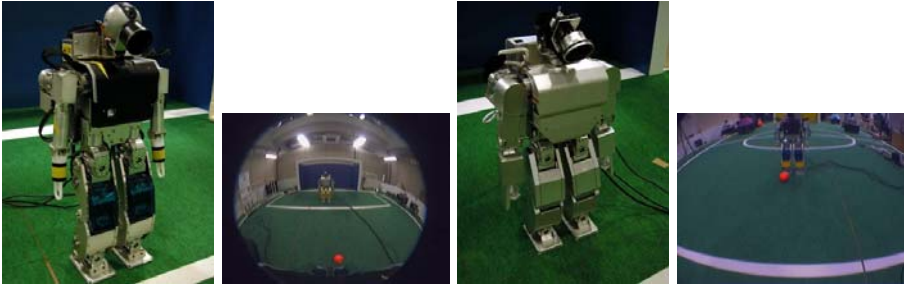


Fig. 1. HOAP-1 with fish-eye lens and HOAP-2 with semi-fish-eye lens

2.2 Task and Assumptions

“Face-to-face pass” can be decomposed into a sequence of different behaviors:

- trapping a ball which is coming to the player,
- approaching to kick a trapped ball, and
- kicking a ball to the opponent.

All these basic behaviors need the appropriate relationship between motion parameters and the environment changes. For example, to trap a ball appropriately, the robots must estimate the arrival time and position of the coming ball. To approach to a kicking position, the robot should know the causal relationship between the walking parameters and the positional change of the objects in its image. Further, to kick a ball to the opponent, the robot must know the causal relationship between the kicking parameters and the direction the kicked ball will go.

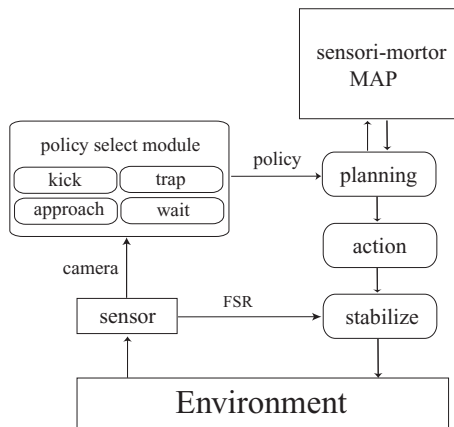


Fig. 2. A system overview

Moreover, basic skills to realize these behaviors should be activated at the appropriate situations. Here, the designer determines these situations to switch the behaviors, and we focus on the skill learning based on optic flow information. Fig. 2 shows an overview of our proposed system.

3 Skill Learning Based on Optic Flow Information

3.1 Ball Trapping

Fig. 4 shows the trapping motion by HOAP-1 acquired by the method described below. In order to realize such a motion, the robot has to predict the position and the arrival time of a ball from its optical flow captured in the robot view. For that purpose, we use a neural network which learns the causal relationship between the position and optical flow of the ball in visual image of a robot and the arrival position and time of the coming ball. This neural network is trained by the data in which a ball is thrown to a robot from the various positions. Fig. 3 shows several prediction results of the neural network after learning. Δx [pixel] and Δt [sec] indicates the errors of the arrival position and the time predicted at each point in the robot's view. Based on this neural network, the robots can activate the trapping motion module with the appropriate leg (right or left) at the appropriate timing (Fig. 4).

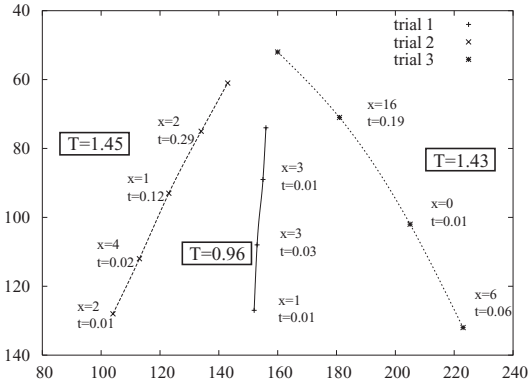


Fig. 3. The prediction of the position and time of a coming ball



Fig. 4. An experimental result of a trapping skill

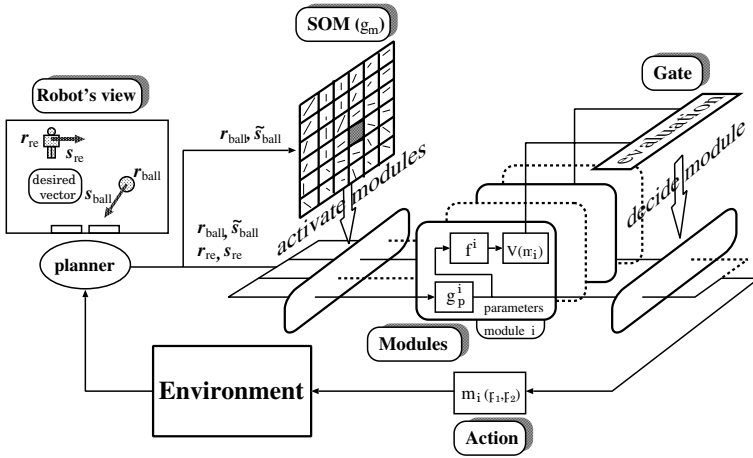


Fig. 5. An overview of the approaching skill

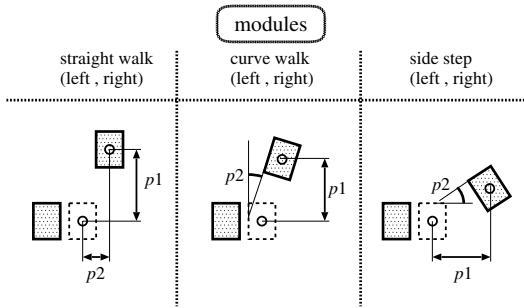


Fig. 6. Motion modules and parameters for approaching

3.2 Ball Approaching

Approaching to a ball is the most difficult task among the three skills because this task involves several motion modules each of which has parameters to be determined. These motions yield various types of image flows depending on the values of the parameters which change continuously. We make use of environmental image flow pattern during various motions to approach to the ball.

Let the motion flow vector Δr at the position r in the robot's view when a robot takes a motion, a . The relationships between them can be written,

$$\Delta r = f(r, a), \tag{1}$$

$$a = g(r, \Delta r). \tag{2}$$

The latter is useful to determine the motion parameters after planning the motion path way in the image. However, it is difficult to determine one motion to

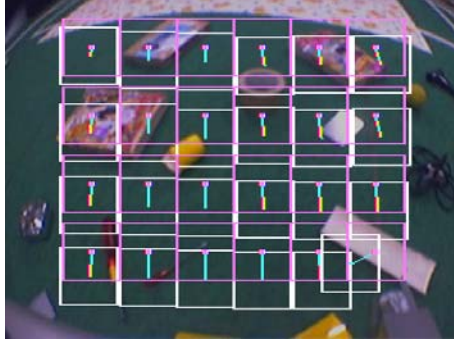


Fig. 7. An example of an optic flow in the robot's view

realize a certain motion flow because different motion modules can produce the same image flow by adjusting motion parameters. Therefore, we separate the description of the relationship between the motion and the image flow into the relationship between the motion module and the image flow, and the relationship between the motion parameters in each module and the image flow (Fig. 5), as follows.

$$m_i = g_m(\mathbf{r}, \Delta\mathbf{r}), \quad (3)$$

$$\mathbf{a}^i = (p_1^i, p_2^i)^T = g_p^i(\mathbf{r}, \Delta\mathbf{r}) \quad (4)$$

$$\Delta\mathbf{r} = f^i(\mathbf{r}, \mathbf{a}^i), \quad (5)$$

where m_i is the index of the i -th motion module and $\mathbf{a}_i = (p_{i1}, p_{i2})^T$ are the motion parameter vector of the i -th motion module. In this study, the motion modules related to this skill consists of 6 modules; *straight walk* (left and right), *curve walk* (left and right), and *side step* (left and right). Each of the modules has two parameters which have real values, as shown in Fig. 6.

Given the desired motion pathway in the robot's view, we can select appropriate module by g_m , and determine the motion parameters of the selected motion module by g_p^i based on the learned relationships among the modules, their parameters, and flows. If the desired image flow yields several motion modules, the preferred motion module is determined by value function.

Images are recorded every step and the image flow is calculated by block matching between the current image and the previous one. The templates for calculating flows are 24 blocks in one image as shown in Fig. 7.

g_m . All of the data sets of the flow and its positional vector in the image, $(\mathbf{r}, \Delta\mathbf{r})$, are classified by the self organizing map (SOM), which consists of 225 (15×15) representational vectors. After the organization, the indices of motion modules are attributed to each representational vector. Fig. 8 shows the classified image vector (the figure at the left side) and the distribution of each module in SOM. This SOM outputs the index of appropriate motion module so that the desired flow vector in the image is realized.

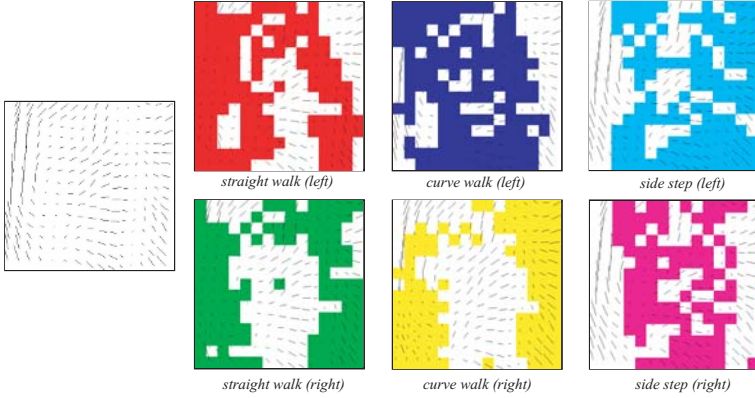


Fig. 8. Distribution of motion modules on the SOM of optic flows

f^i, g_p^i . The forward and inverse functions that correlate the relationship between the motion parameters in each module and the image flow, f^i, g_p^i , are realized by a simple neural network. The neural network in each module is trained so that it outputs the motion parameters when the flow vector and the positional vector in the image are input.

Planning and Evaluation Function. In this study, the desired optic flow in the robot's view for the ball and the receiver, s_{ball}, s_{re} , are determined as a vector from the current position of a ball to the desired position (kicking position) in the robot's view, and as the horizontal vector from the current position to the vertical center line, respectively. The next desired optic flow of a ball to be realized, \tilde{s}_{ball} , is calculated based on these desired optic flows,

$$n_{step} = \|s_{ball}\| / \Delta r_{max}, \quad (6)$$

$$\tilde{s}_{ball} = s_{ball} / n_{step}, \quad (7)$$

where Δr_{max} is the maximum length of the experienced optical flow. This reference vector is input to the module selector, g_m , and the candidate modules which can output the reference vector are activated. The motion parameters of the selected module are determined by the function g_p^i ,

$$a^i = g_p^i(x_{ball}, \tilde{s}_{ball}), \quad (8)$$

where x_{ball} is the current ball position in the robot's view. When the module selector outputs several candidates of modules, the evaluation function depending on the task, $V(m_i)$, determines the preferred module. In this study, our robots have to not only approach to a ball but also take an appropriate position to kick a ball to the other. For that, we set the evaluation function as follows,

$$selected\ module = \arg\min_{i \in modules} \left[\|\tilde{s}_{ball} - f^i(x_{ball}, a^i)\| + k \|s_{re} - n_{step} f^i(x_{re}, a^i)\| \right], \quad (9)$$

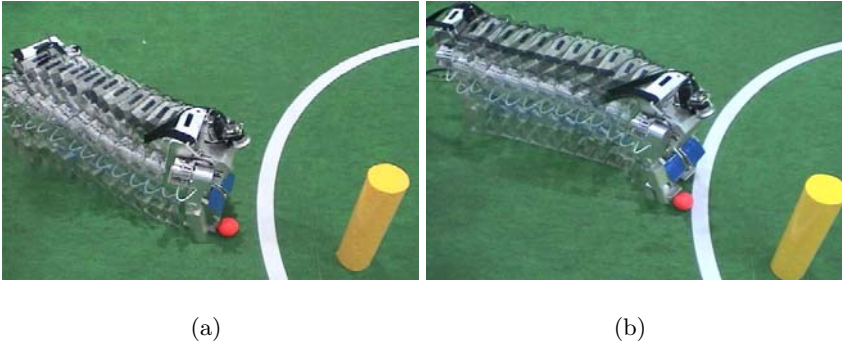


Fig. 9. Experimental results of approaching to a ball

where k is the constant value, and r_{re} is the current position of the receiver in the robot’s view.

Fig. 9 shows experimental results of approaching to a ball. A robot successfully approaches to a ball so that the hypothetical opponent (a pole) comes in front of it.

3.3 Ball Kicking to the Opponent

It is necessary for our robots to kick a ball to the receiver very precisely because they cannot sidestep quickly. We correlate the parameter of kicking motion with the trace of the kicked ball in the robot’s view so that they can kick to each other precisely. Fig. 10 shows a proposed controller for kicking.

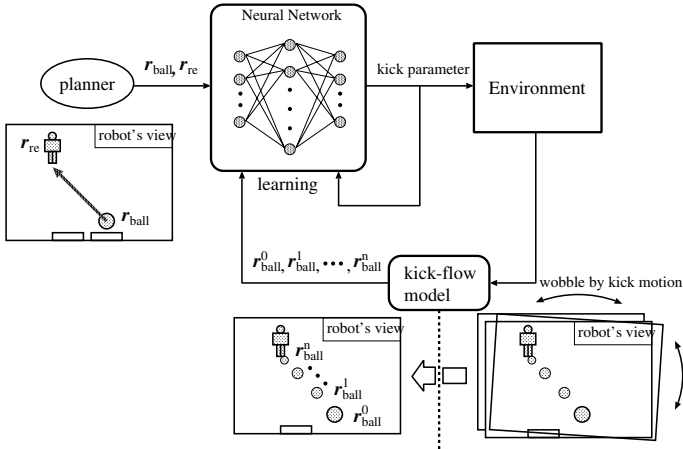
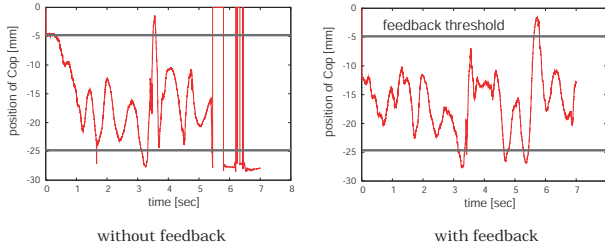
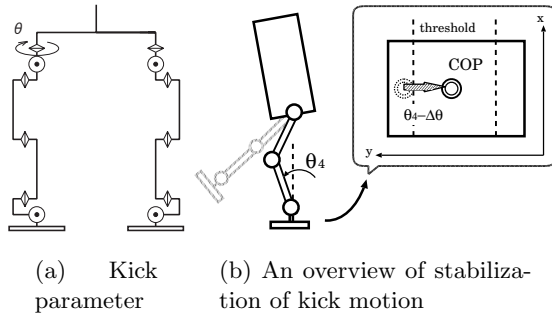


Fig. 10. The system for kicking skill



(c) The trajectories of CoP of the support leg during kicking motion

Fig. 11. The parameter and the stabilization of kicking

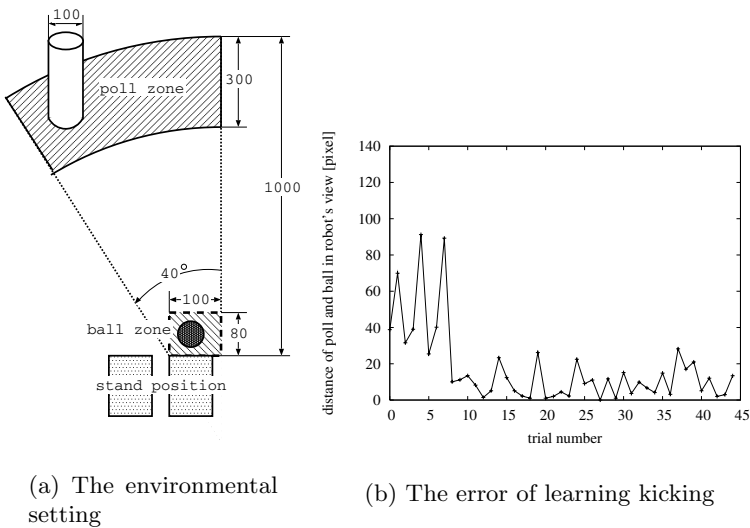


Fig. 12. The environmental setting and the learning curve for kicking



Fig. 13. An experimental result of kicking a ball to the pole

The kicking parameter is the hip joint angle shown in Fig. 11(a). The quick motion like kicking changes its dynamics depending on its motion parameter. The sensor feedback from the floor reaction force sensors is used for stabilizing the kicking motion. The displacement of the position of the center of pressure (CoP) in the support leg is used as feedback to the angle of the ankle joint of the support leg (see Fig. 11(b)). Fig. 11(c) shows the effectiveness of the stabilization of the kicking motion. The initial ball position and the parameter of the kicking motion affects sensitively the ball trace in the robot’s view. To describe the relationship among them, we use a neural network, which is trained in the environment where the pole (10 [cm]) is put about 1 [m] in front of the robot (Fig. 13(a)). The trace of the ball (the effects of the self motion is subtracted) is recorded every 100 [msec], and the weights in the neural network are updated every one trial. Fig. 13(b) shows the time course of error distance between target pole position and kicked ball in the robot’s view. It shows that the error is reduced rapidly within 20 [pixel], which is the same size of the width of the target pole. Fig. 13 shows the kicking performance of the robot.

4 Integration of the Skills for Face-to-Face Pass

To realize passing a ball between two humanoids, the basic skills described in the previous chapter are integrated by the simple rule as shown in Fig. 14.

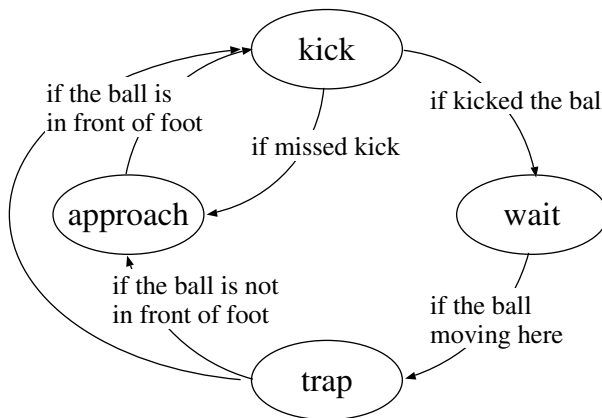


Fig. 14. The rule for integrating motion skills

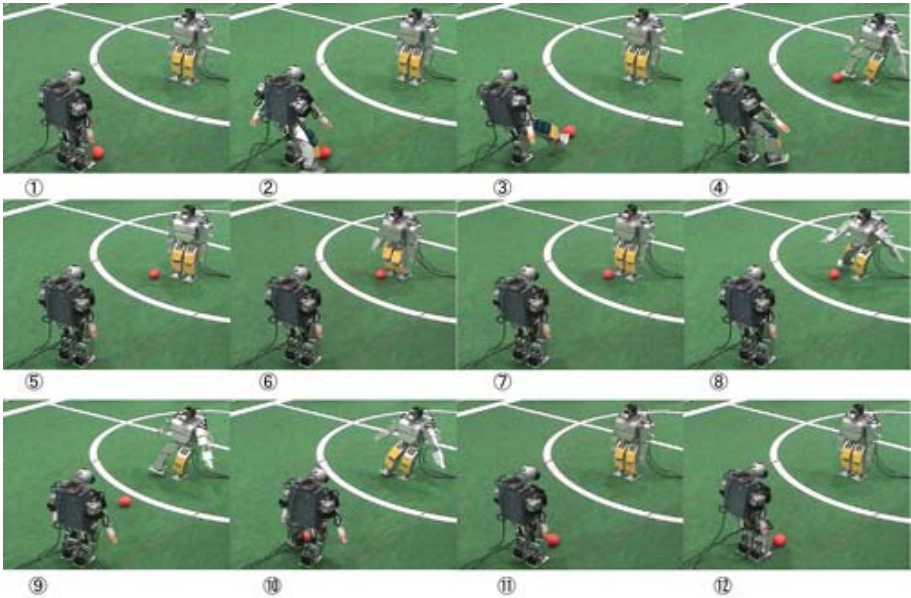


Fig. 15. An experimental result of passes between two humanoids

Fig. 15 shows the experimental result. Two humanoids with different body and different camera lens realize the appropriate motions for passing a ball to each other based on their own sensorimotor mapping. The passing lasts more than 3 times.

5 Conclusions

In this paper, acquiring basic skills for passing a ball between two humanoids is achieved. In each skill, optic flow information is correlated with the motion parameters. Through this correlation, a humanoid robot can obtain the sensorimotor mapping to realize the desired skills. The experimental results show that a simple neural network quickly learns and models well the relationship between optic flow information and motion parameters of each motion module. However, there remain the harder problems we skip in this paper. First is skill decomposition problem; it is concerning about how to determine what are the basic skills for the given task. Second is planning, that is how to organize each motion module to achieve the given task. In this paper, we assume skill decomposition and planning are given in advance. Combining the learning in each skill level with that in higher level is the next problem for us.

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