# A Humanoid Approaches to the Goal – Reinforcement Learning Based on Rhythmic Walking Parameters

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**Abstract.** This paper presents a method for generating vision-based humanoid behaviors by reinforcement learning with rhythmic walking parameters. The walking is stabilized by a rhythmic motion controller such as CPG or neural oscillator. The learning process consists of two stages: the first one is building an action space with two parameters (a forward step length and a turning angle) so that infeasible combinations of them are inhibited. The second one is reinforcement learning with the constructed action space and the state space consisting of visual features and posture parameters to find feasible action. The method is applied to a situation of the RoboCupSoccer Humanoid league, that is, to reach the ball and to shoot it into the goal. Instructions by human are given to start up the learning process and the rest is completely self-learning in real situations.

## 1 Introduction

Since the debut of Honda humanoid [3], the research community for biped walking has been growing and various approaches have been introduced. Among them, there are two major trends in the biped walking. One is model based approach with ZMP (zero moment point) principle [4] or the inverted pendulum model [14] both of which plan the desired trajectories and control their bipeds to follow them. In order to stabilize the walking, these methods need very precise dynamics parameters for both the robot and its environment.

The other one is inspired by the findings [2] in neurophysiology that most animals generate their walking motions based on the central pattern generator (hereafter, CPG) or neural oscillator. CPG is a cluster of neural structures that oscillate each other under the constraint of the relationships in their phase spaces, and generates rhythmic motions that interact with the external environment and the observed motion can be regarded as a result of the entrainment between robot motion and the environment. This sort of approach does not need model parameters that are as precicise as ZMP or the inverted pendulum.

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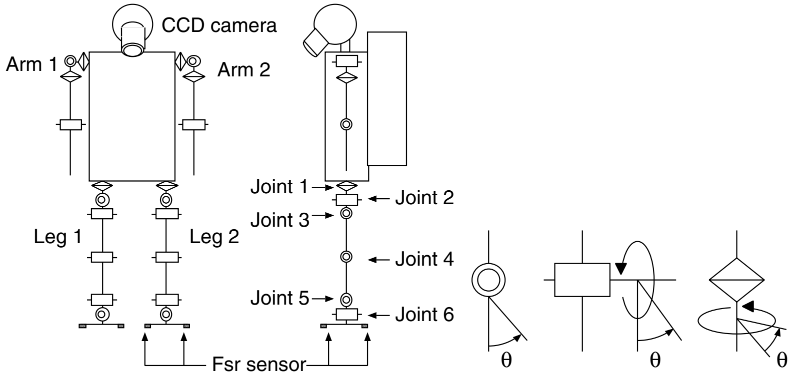



(a) Model of robot (b) Mark of joint

**Fig. 1.** A model of biped locomotion robot

Taga et al. [11] gave the mathematical formulation for neural oscillator, constructed a dynamic controller for biped walking on the sagittal plane, and showed the simulation results which indicated that his method could generate stable biped motions similar to human walking. Others extended his method to three dimensions [8] and adaptive motion on the slope by adjusting the neural oscillator [1].

The second approach seems promising for adaptation against changes in the environment. To handle more complicated situations, the visual information has been involved. Taga [12] studied how the robot can avoid an obstacle by adjusting the walking pattern assuming that the object height and the distance to it can be measured by the visual information. Fukuoka et al. [5] also adjusted CPG input so that a quadruped can climb over a step through the visual information. In these methods, however, the adjusting parameters were given by the designer in advance. Therefore, it seems difficult to apply to more dynamic situations, and learning method seems necessary.

This paper presents a method for generating vision-based humanoid behaviors by reinforcement learning with rhythmic walking parameters. A rhythmic motion controller such as CPG or neural oscillator stabilizes the walking [13]. The learning process consists of two stages: first one is building an action space with two parameters (a forward step width and a turning angle) so that infeasible combinations of them are inhibited. The second one is reinforcement learning with the constructed action space and the state space consisting of visual features and posture parameters to find feasible action. The method is applied to a situation of the RoboCupSoccer Humanoid league [6], that is, to approach the ball and to shoot it into the goal. Instructions by human are given to start up the learning process and the rest is solely self-learning in real situations.

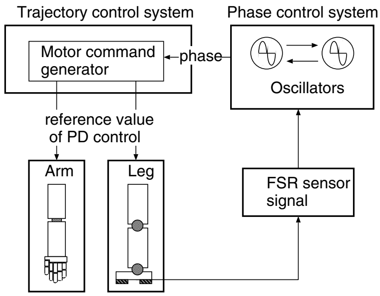



**Fig. 2.** A walking control system

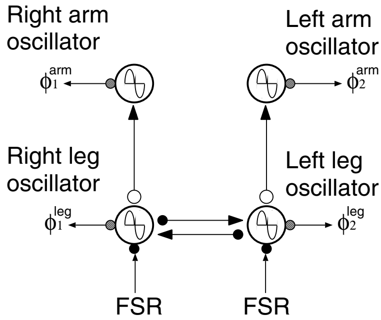



**Fig. 3.** A phase control system

## 2 Rhythmic Walking Controller

### 2.1 Biped Robot Model

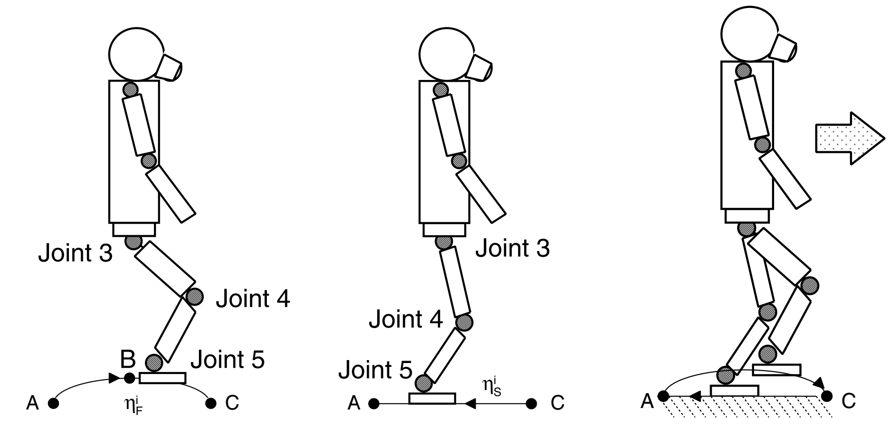
Fig. 1 shows a biped robot model used in the experiment which has a one-link torso, two four-link arms, and two six-link legs. All joints rotate with a single DoF rotation. Each foot has four FSRs to detect reaction force from the floor and a CCD camera with a fish-eye lens is attached at the top of the torso.

### 2.2 Rhythmic Walking Controller Based on CPG Principle

Tsujita and Tsuchiya [13] designed a rhythmic walking controller based on CPG principle and generated walking motions adaptive to the environment through the mutual entrainment between non-linear neural oscillators. Following their design principle, we build a controller which consists of trajectory and phase ones to control reciprocation of each leg. (see Fig. 2). The former drives motors attached to joints according to the motor command from the latter which consists of two oscillators. The phase controller receives the feedback signal of reaction force from the floor through the FSRs attached at the soles.

The stable walking motion is realized as follows.

1. Each leg motion has two kinds of modes: a free leg mode and a support leg one both of which trajectories are specified by the designer in advance (see Fig. 4).
2. In each mode, the joint trajectories are given as a phase function in terms of the corresponding neural oscillators.
3. Mode switching is triggered by phase shift of the free leg caused by the ground contact information from the FSRs. That is, if the free leg contacts with the floor, the phase of the free leg (the support leg, too) is accelerated, and mode switch (free leg $\longleftrightarrow$ support leg) happens.
4. Various kinds of walking are generated with two parameters: a forward step length $\beta$ and a turning angle $\alpha$ (see Fig. 5).




(a) Trajectory of free leg (b) Trajectory of support leg (c) Trajectory of leg

**Fig. 4.** Trajectories of the leg

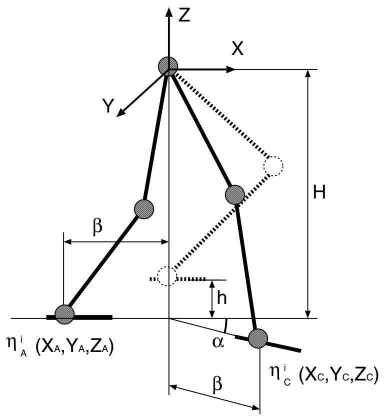



**Fig. 5.** Waking parameters

# 3 Reinforcement Learning with Rhythmic Walking Parameters

## 3.1 Principle of Reinforcement Learning

Recently, reinforcement learning has been receiving increased attention as a method for robot learning with little or no *a priori* knowledge and higher capability of reactive and adaptive behaviors. Fig. 6 shows the basic model of robot-environment interaction [10], where a robot and an environment are modelled by two synchronized finite state automatons interacting in a discrete time

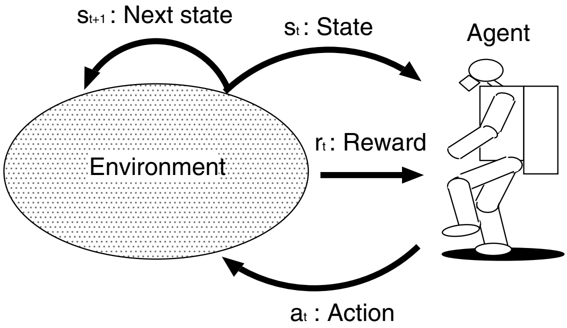



**Fig. 6.** Basic model of agent-environment interaction

cyclical processes. The robot senses the current state $s_t \in \boldsymbol{S}$ of the environment and selects an action $a_t \in A$. Based on the state and action, the environment makes a transition to a new state $s_{t+1}$ and generates a reward $r_{t+1}$ that is passed back to the robot. Through these interactions, the robot learns a purposive behavior to achieve a given goal. In order for the learning to converge correctly, the environment should satisfy the Markovian assumption that the state transition depends on only the current state and the taken action. The state transition is modelled by a stochastic function $\boldsymbol{T}$ which maps a pair of the current state and the action to take to the next state ($\boldsymbol{T} : \boldsymbol{S} \times \boldsymbol{A} \rightarrow \boldsymbol{S}$). Using $\boldsymbol{T}$, the state transition probability $P_{s_t,s_{t+1}}(a_t)$ is given by

$$P_{s_t,s_{t+1}}(a_t) = Prob(\boldsymbol{T}(s_t, a_t) = s_{t+1}). \tag{1}$$

The immediate reward $r_t$ is given by the reward function in terms of the current state by $R(s_t)$, that is $r_t = R(s_t)$. Generally, $P_{s_t,s_{t+1}}(a_t)$ (hereafter $\mathcal{P}^a_{ss'}$) and $R(s_t)$ (hereafter $\mathcal{R}^a_{ss'}$) are unknown.

The aim of the reinforcement learner is to maximize the accumulated summation of the given rewards (called *return*) given by

$$return(t) = \sum_{n=0}^{\infty} \gamma^n r_{t+n}, \tag{2}$$

where $\gamma\,(0 \leq \gamma \leq 1)$ denotes a discounting factor to give the temporal weight to the reward.

If the state transition probability is known, the optimal policy which maximizes the expected *return* is given by finding the optimal value function $V^*(s)$ or the optimal action value function $Q^*(s, a)$ as follows. The derivation of them can be found elsewhere [10].

$$\begin{aligned} V^*(s) &= \max_a E\{r_{t+1} + \gamma V^*(s_{t+1}) | s_t = s, a_t = a\} \\ &= \max_a \sum_{s'} \mathcal{P}^a_{ss'} \left[\mathcal{R}^a_{ss'} + \gamma V^*(s')\right] \end{aligned} \tag{3}$$

$$\begin{aligned} Q^*(s,a) &= E\{r_{t+1} + \gamma \max_{a'} Q^*(s_{t+1}, a') | s_t = s, a_t = a\} \\ &= \sum_{s'} \mathcal{P}^a_{ss'} \left[ \mathcal{R}^a_{ss'} + \gamma \max_{a'} Q^*(s', a') \right] \end{aligned} \tag{4}$$

In this paper, the learning module examines the state transition when both feet contact with the ground. The state space, **S**, consists of the visual information $s_v$ and the robot posture $s_p$, and the action space consists of two parameters of rhythmic walking. Details are explained in the following subsections.

### 3.2 Construction of Action Space Based on Rhythmic Parameters

The learning process has two stages. The first one is to construct the action space consisting of feasible combinations of two rhythmic walking parameters ($\alpha$, $\beta$). To do that, we prepared the three-dimensional posture space $s_p$ in terms of the forward length $\beta$ (quantized into four lengths: 0, 10, 35 60 [mm]), the turning angle $\alpha$ (quantized into three angles: -10, 0, 10 [deg].) both of which correspond to the result of the execution of the previous action command, and the leg side (left or right). Therefore, we have 24 kinds of postures. First, we have constructed the action space of the feasible combinations of ($\alpha$, $\beta$) excluding the infeasible ones which cause collisions with its own body. Then, various combinations of actions are examined for stable walking in the real robot. Fig. 7 shows the feasible actions (empty boxes) for each leg corresponding to the action, which determines the resultant posture of the next step. Due to the differences in physical properties between two legs, the constructed action space was not symmetric although it should be theoretically.

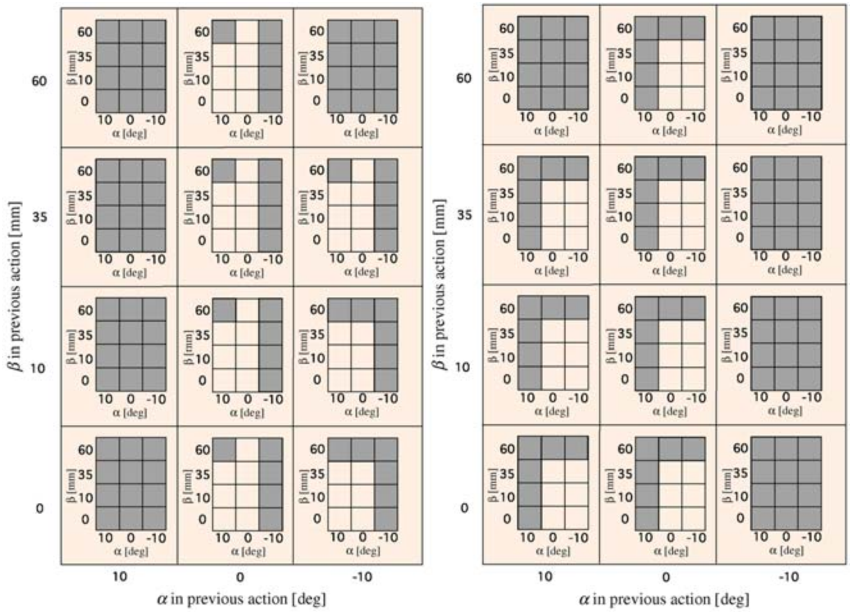
### 3.3 Reinforcement Learning with Visual Information

Fig. 8 shows an overview of the whole system which consists of two layers: adjusting walking based on the visual information and generating walking based on neural oscillators. The state space consists of the visual information $s_v$ and the robot posture $s_p$, and adjusted action $a$ is learned by dynamic programming method based on the rhythmic walking parameters ($\alpha$, $\beta$). In a case of ball shooting task, $s_v$ consists of ball substates and goal substates both of which are quantized as shown in Fig. 9. In addition to these substates, we add two more substates, that is, "the ball is missing" and "the goal is missing" because they are necessary to recover from loosing their sight.

Learning module consists of a planner which determines an action $a$ based on the current state $s$, a state transition model which estimates the state transition probability $\mathcal{P}^a_{ss'}$ through the interactions, and a reward model (see Fig. 10). Based on DP, the action value function $Q(s,a)$ is updated and the learning stops when no more changes in the summation of action values.

$$Q(s,a) = \sum_{s'} \mathcal{P}^a_{ss'} [\mathcal{R}_s + \gamma \max_{a'} Q(s', a')], \tag{5}$$

where $\mathcal{R}_s$ denotes the expected reward at the state $s$.




(a) left leg (b) right leg

**Fig. 7.** Experimental result of action rule

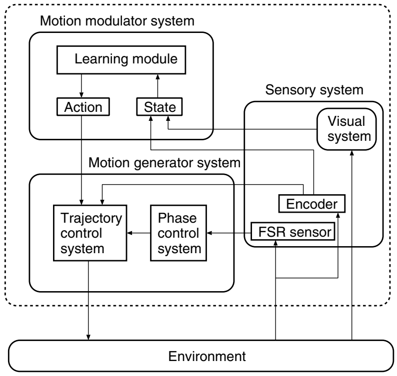
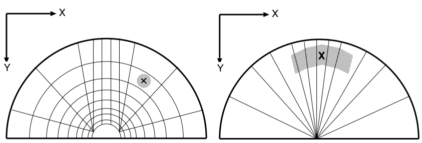



**Fig. 8.** Biped walking system with visual perception




(a) State space of ball (b) State space of goal

**Fig. 9.** State space of ball and goal

# 4 Experiments

## 4.1 Robot Platform and Environment Set-Up

Here, we use a humanoid platform HOAP-1 by Fujitsu Automation LTD. [9] attaching a CCD camera with a fish-eye lens at the head. Figs. 11 and 12 show a

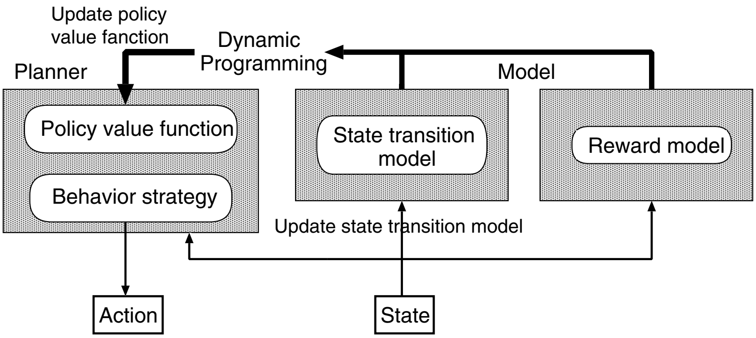



**Fig. 10.** A learning module

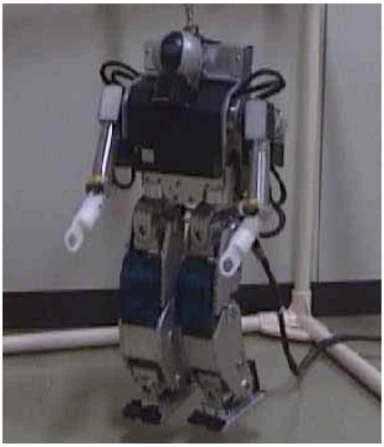


**Fig. 11.** HOAP-1

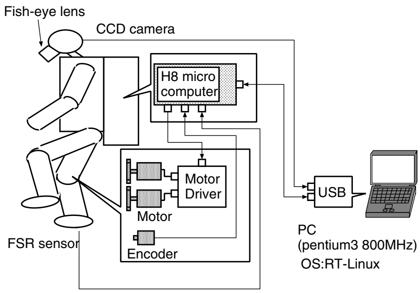



**Fig. 12.** An overview of the robot system

picture and a system configuration, respectively. The height and the weight are about 480[mm] and 6[kg], and each leg (arm) has six (four) DoFs. Joint encoders have high resolution of 0.001[deg/pulse] and reaction force sensors (FSRs) are attached at soles. The colour image processing to detect an orange ball and a blue goal is performed on the CPU (Pentium3 800MHz) under RT-Linux. Fig. 13 shows the on-board image.

The experimental set-up is shown in Fig. 14 where the initial robot position is inside the circle whose center and radius are the ball position and 1000 [mm], respectively, and the initial ball position is located less than 1500 [mm] from the goal of which width and height are 1800 [mm] and 900 [mm], respectively. The task is to take a position just before the ball so that the robot can shoot a ball into the goal. Each episode ends when the robot succeeds in getting such positions or fails (touches the ball or the pre-specified time period expires).

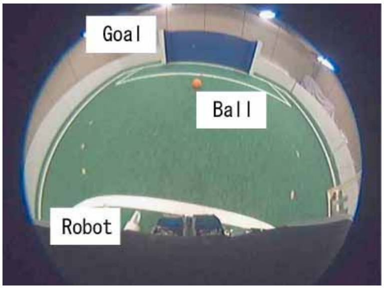



**Fig. 13.** Robot's view (CCD camera image through fish-lens)

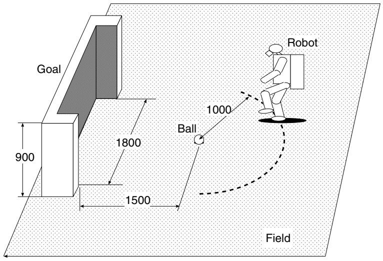



**Fig. 14.** Experimental environment

### 4.2 Experimental Results

One of the most serious issues in applying the reinforcement learning method to real robot tasks is how to accelerate the learning process. Instead of using Q-learning that is most typically used in many applications, we use a DP approach based on the state transition model $\mathcal{P}^a_{ss'}$ that is obtained separately from the behavior learning itself. Further, we give the instructions to start up the learning, more correctly, during the first 50 episodes (about a half hour), the human instructor avoids the useless exploration by directly specifying the action command to the learner about 10 times per one episode. After that, the learner experienced about 1500 episodes.

Owing to the state transition model and initial instructions, the learning converged in 15 hours, and the robot learned to get the right position from any initial positions inside the half field. Fig. 15 shows the learned behaviors from different initial positions. In Fig. 15, the robot can capture the image including both the ball and the goal from the initial position while in Fig. 15 (f) the robot cannot see the ball or the goal from the initial position.

## 5 Concluding Remarks

A vision-based behavior of humanoid was generated by reinforcement learning with rhythmic walking parameters. Since the humanoid generally has many DoFs, it is very hard to control all of them. Instead of using these DoFs as action space, we adopted rhythmic walking parameters, which drastically reduces the search space and therefore the real robot learning was enabled in reasonable time. In this study, the designer specified the state space consisting of visual features and robot postures. State space construction by learning is one of the future issues.

## Acknowledgments

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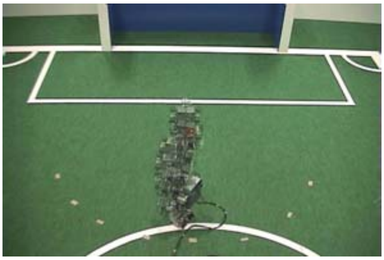
(a) Result 1

(b) Result 2



(c) Result 3

(d) Result 4

(e) Result 5

(f) Result 6

**Fig. 15.** Experimental results

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