A CONCEPT LEARNING BASED APPROACH TO MOTION CONTROL FOR HUMANOID ROBOTS

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Keywords: Humanoid robot, learning-based motion control, concept learning.

Abstract: This paper proposes a concept learning-based approach to motion control for humanoid robots. In this approach, the motion control system is implemented with *decision tree learner* for the acquisition of balancing property of itself body and movement and *depth first search technique* for the motion control based on the knowledge concerning balance and stability in the motion. Some performance results by humanoid robot HOAP-1 is reported: stable and anti-tumble motions to stand up from a chair. This paper also reports some performance for the change in the environments; stand up from a chair on slope and different in height.

1 INTRODUCTION

Recently, the research of humanoid has been attracting much attention in robotics. The latest research and development brings several humanoid biped robots in our lives (e.g., (Murase et al., 2001), (Kuroki et al., 2002)). Sophisticated motion control techniques for symmetric and cyclic motion, such as two-legged locomotion (Taga, 1995), and asymmetric various movement of entire body, such as dance and body exercise (Noritake et al., 2003), have been performed by the humanoid robots. For these technologies, some learning-based approaches, such as reinforcement learning, neural network and so on, have made a substantial contribution to motion control for humanoids (e.g., (Morimoto and Doya, 2000), (Capi et al., 2002)). Reinforcement learning and neural network approaches are, however, highly vulnerable to a small change in the environments. The change imposes re-learning, thereby making the motion control computationally very expensive. The advantage of humanoids should be a diversity of motion because of their link structure with high degree of freedom. In this paper, we, thus, propose a concept learning based motion generation system. The aim of this approach is to discover the knowledge for generating the stable motion in balance. The system can generate a stable and anti-tumble motion by the concept learning and the searching in the motion space: extracting some generalized motion guideposts by decision tree learner and motion generation with tracking the guidepost by depth-first search. The system attempt to reduce the limitation of a motion variation and executive environment.

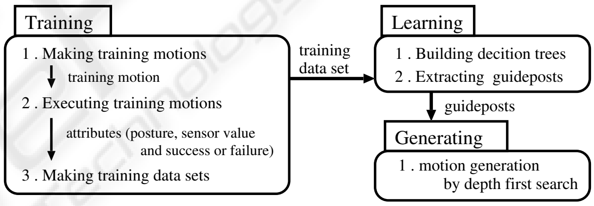


Figure 1: The outline of the system.

2 THE LINK MODEL AND THE MOTION STABILITY VALUES

Preliminary to the description of our system, we give a link model of our humanoid robot and its motion stability values.

A posture of a humanoid robot is uniquely decided from joint angles and body gradient. At arbitrary time t, posture of humanoid robot is uniquely determined by its joint angles and its body gradient. A time series of postures becomes a motion of the humanoid.

*Motion stability value*s are criteria of motion stability. These value are position data concerning state of the balance, such as center of mass (COM) and zero moment point (Vukobratovic et al., 1970) (ZMP), or sensor value, such as body accelerate sensor.

Kuwayama K., Kato S. and Itoh H. (2004).
A CONCEPT LEARNING BASED APPROACH TO MOTION CONTROL FOR HUMANOID ROBOTS.
In *Proceedings of the First International Conference on Informatics in Control, Automation and Robotics*, pages 335-338
DOI: 10.5220/0001142903350338

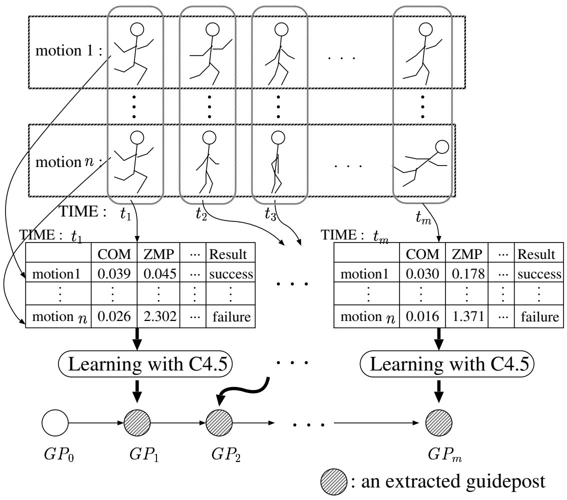


Figure 2: Training data sets for learning.

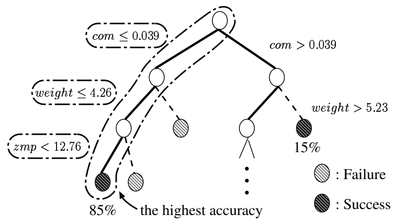


Figure 3: A model of decision tree by concept learning.

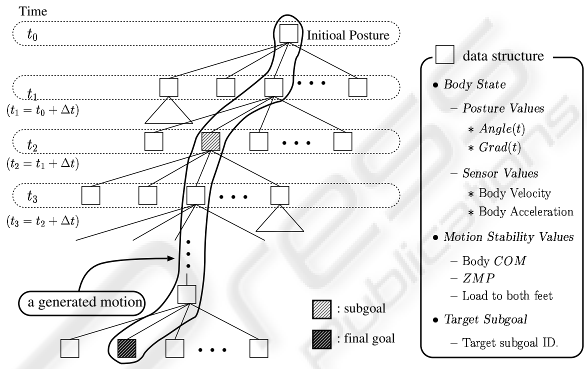


Figure 4: A model of search tree by our system.

3 A CONCEPT LEARNING-BASED MOTION GENERATION SYSTEM

The section describes our motion generation system for humanoid robots. This system can generate a stable and anti-tumble motion which transforms the robot from an initial posture into a target posture. Figure 1 shows the outline of the system. The system has three parts: *Training*, *Learning* and *Generating* part. Each part of the system is described below.

Training Part
Firstly, the system makes training data sets for learning part.

1. Preliminary to motion generation, lots of motions, by which the robot moves between the initial and the target posture, are made. These motions are independent of feasibility consideration.
2. The robot, then, executes the motions. The motions are, after that, classified into two groups: *positive* or *negative* examples, according to the feasibility of the motions.
3. Each example has some attributes as the reason for the classification. *Motion Stability Values* are considered as the attributes.

Motion and sensor values are time-series data. In this paper, the training data set is decomposed by time (see Figure 2).

Learning Part
Secondly, the system extracts some guideposts for stable and anti-tumble motion from training data sets by a concept learning system C4.5 (Quinlan, 1993).

1. The system builds a decision tree from a training data set by C4.5, which is generally considered to be one of the best empirical decision tree learners. It should be noticed that decision trees are built at arbitrary time intervals.
2. The highest accuracy path from a root node to a successful leaf is extracted as a guidepost from each of the decision trees. One guidepost has some conditions of the *Motion Stability Value*s for the robot so as to execute the motion stably (see Figure 3).

Through the above procedure, guideposts are composed in a time-series. A robot motion is generated by successively tracking the guideposts as subgoal from initial posture.

Generating Part
The system, finally, generates a motion by search in the motion space.

1. Depth first search generates sequences of joint angles to transform the robot into the target posture.

In general for humanoid robots, the search space for motion generation exponentially explodes because of the large numbers of DOFs. In our system, search space is reduced by tracking the guideposts. The search tree generated by our system is intuitively illustrated in Figure 4. A node of the search tree has the data structure written on the right side of the figure. A *subgoal* means an intermediate guidepost for target posture.

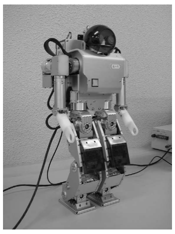


Figure 5: HOAP-1.

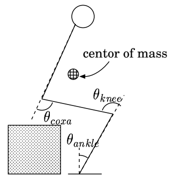


Figure 6: The link structure for standing motion.

Table 1: Learning Results

GP_1	$COM_x > -0.035$	GP_3	$COM_z > 0.215$
	$COM_x <= -0.026$	GP_4	$COM_z > 0.215$
GP_2	$COM_x > -0.056$	GP_5	$COM_z > 0.233$
	$COM_x <= 0.018$	GP_F	$COM_x = 0.008$
	$COM_z > 0.197$		$COM_z = 0.237$

4 EXPERIMENT

The section gives a performance of our system. The target motion is to stand up from a chair.

4.1 Humanoid Robot

In this paper, we consider the motion control of a humanoid robot, HOAP-1 (Humanoid for Open Architecture Platform) produced by Fujitsu(Murase et al., 2001), shown in Figure 5. The total weight is 5.8 (kg) and the height is 480 (mm). HOAP-1 has 20 DOFs in total, 6 in each leg and 4 in each arm.

4.2 Standing Motion from a Chair

In this paper, we suppose that standing motion from a chair is made by changing the servo motor of coxa,

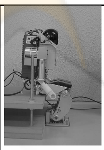
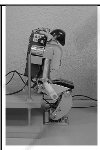
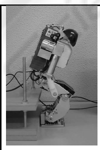
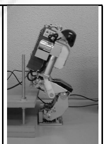
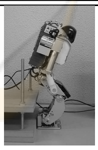
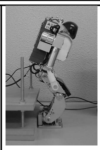
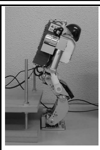
				
guidepost ID	0	1	1	1
time (msec)	0	500	1000	1250
				
guidepost ID	1	5	FINAL	
time (msec)	2000	3000	3250	

Figure 7: The snapshot of a standing motion generated by the system.

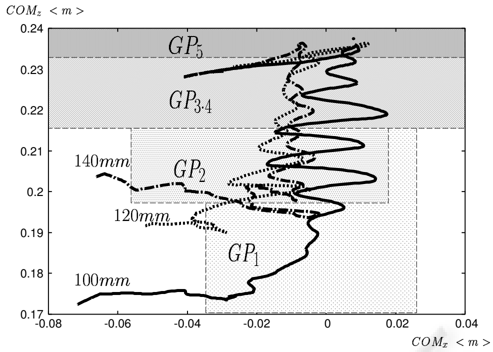


Figure 8: Trajectory of COM changing the height of a chair.

knee and ankle joint. The motion is supposed to be symmetric. The link structure is, thus, simplified to three links model shown in Figure 6. A training motion is made by the linear interpolation at twice between a sitting posture and a middle posture and between a middle posture and a standing posture for 2000 (msec). The height of the chair on a flat floor is set 120 (mm). We have prepared 477 motions by changing the middle posture. HOAP-1 has executed these motions in advance to the motion generation, and then the motions are classified into two groups: success or failure. Horizontal and vertical components of COM are given as the attributes of the motions. We have made 5 training data sets of 477 examples, and built 5 decision trees and 5 guideposts by C4.5. Table 1 shows the guideposts for standing from the chair. HOAP-1 stood up from a 120(mm) tall chair on a flat floor by tracking these guideposts.

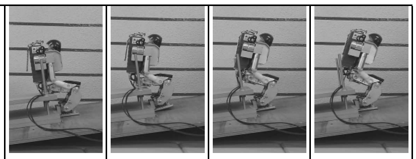
We have made some experiments that the some changes in the environment are imposed on the motion generation. In these experiments, it should be noticed that each of the guideposts is the same with the guidepost extracted from the above learning(see Table 1); there is no re-learning, that is, these experiments is to verify the admissibility of our system for the changes in the environment. The results may indicate how learned knowledge is generalized, and how search control recovers the mistracking of guideposts.

Stand up from a Chair in Different Height

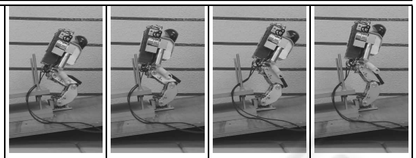
We have made some experiments for the stand up motion by changing the height of a chair. For a 100 (mm) (i.e., lower than that for learning) tall chair, GP_1 and $GP_{3\cdot4}$ were most effective for the motion generation. For a 140 (mm) (i.e., higher than that for learning) tall chair, GP_1 and GP_2 were most effective. Figure 8 shows the trajectory of COM of HOAP-1 when it executes the motions obtained by search.

Stand up from a Chair on a Slope

We have made some experiments for the stand up motion from a chair on forward and backward slopes. In this particular case, the system can generate the stand up motion with only GP_5. Figure 9 shows the snapshots of a standing motion by our system, where the gradient of ground is 10.0 (deg) backward. In this particular case, the system can generate the stand up motion with only GP_1 and $GP_{3\cdot4}$. Figure 10 shows the trajectory of the gradient of HOAP-1 body when it executes the motions obtained by search. In the figure, solid, dashed and dotted lines show the trajectory of the gradient of HOAP-1's body standing up from chair on the flat, the forward slope and the backward slope, respectively. The two broken lines, at the beginning of the motion, show that the gradients of the body on the slopes are both different from that on the flat. The difference corresponds to the gradient of the slope. This is obvious, for HOAP-1 is sitting on a chair on the slope. Through the movement, the difference of the gradient is attenuated gradually. The results indicates that the motion control adapts the motion to the different environments.



guidepost ID	0	1	1	1
time (msec)	0	1000	2000	3000



guidepost ID	5	5	5	FINAL
time (msec)	3500	4250	5000	6250

Figure 9: The snapshot of a standing motion generated by the system, where the ground has gradient of 10.0 (deg) backward.

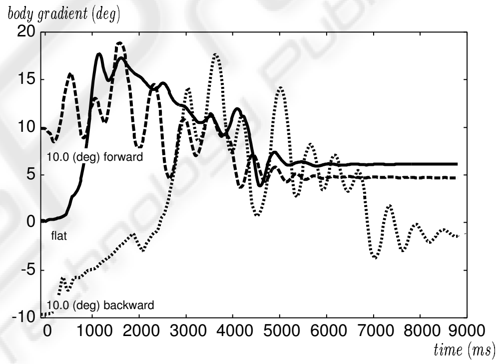


Figure 10: Trajectory of gradient of the body changing gradient of the ground.

5 CONCLUSION

This paper proposed a concept learning-based approach to motion control for humanoid robots. The motion generation system had been implemented with decision tree learner C4.5 and depth first search technique. Some stable and anti-tumble motions to stand up from a chair were performed by humanoid robot HOAP-1. In future work, we will dedicate to the improvement of our system for more complex motions and to the investigation of the relations of the suitable number between guideposts and examples for learning.

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