The 2010 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 18-22, 2010, Taipei, Taiwan

Locomotion Transition Scheme with Instability Evaluation using Bayesian Network

Hiroyoshi Sawada, Kosuke Sekiyama, Tadayoshi Aoyama, Yasuhisa Hasegawa, and Toshio Fukuda

***Abstract*— The applicative field of activities of robots which have only one locomotion strategy is limited. As a mean of enhancing the mobile range, it is necessary to have various locomotion modes. Therefore, we focus on dynamic transitions between several kinds of locomotion modes adapting to environmental changes. In this paper, we aim to realize a stable locomotion along some unknown test courses with transition between biped and quadruped walks. To achive this transition, we propose a method to get environmental information and internal conditions. Robot plans locomotion based on recognition of test courses and estimate stability of walking using Bayesian Network. The effectiveness of proposed method is verified by experiments.**

I. INTRODUCTION

Recently, robots which work in human society have been developed, such as entertainment robots and lifestyle support robots. These robots need to have greater locomotion adaptability than industrial robots designed for a task, because there are various terrains in human society, such as stairs and slopes. Therefore, robots have to recognize terrain and perform stable locomotion autonomously. In walking robots need to estimate realization of performance and they have to modify their gait depending it. Many studies on locomotion adaptability have been carried out.

A leg-wheel robot which can move on unknown rough terrains by using only information of internal sensors has been developed [1]. This robot has an advantage that it can use several locomotion modes adapting to various terrains. The robot cannot obtain environmental information with only internal sensors until it moves there. If external sensors are also used for recognition, the robot can estimate terrain and select locomotion mode in advance. As another example of adaptation to environment, behavior transitions between biped and quadruped walk based on gradient of slopes have been demonstrated by using the bifurcation phenomenon [2]. Aoi et al. developed a locomotion control scheme of the gait change from quadruped to biped using nonlinear oscillators and verified the performance of the proposed control system experimentally [3], [4]. However, these works don't have system which modify robot's gait adjusted to environment. Against this background, we have developed Multi-locomotion robot [5] (Fig. 1). With this robot, we aim to realize adaptive locomotion transition based on environmental recognition. Therefore, this robot has several locomotion modes such as biped and quadruped walk, climbing, and brachiation. There have been proposals of control methods for several locomotion modes [6]–[9]. Autonomous transition between these locomotion modes based on environmental recognition and evaluation of internal models is the current task.

Then, we focus on making option on robot's gait based on both recognition of terrain and estimation of gait performance. In this paper, we aim to realize robust locomotion in unknown test courses, so robots recognize a slope or a step and plan to locomotion. In the next place they need to know whether they realize the plan or not. In robotics system there is uncertainness. Since it influence on realization of performance, we have to deal with uncertainty. This uncertainty is classified into four categories. First one is the uncertainty caused by motion. For example, it's approximation of motion algorithm. Most robots have models to simplify calculating dynamics. So this gives robot systems uncertainty because there are difference between a reality robot shape and a robot model. Second uncertainty is about recognition is accuracy of sensors, effective ranges of sensor or abstraction of environment. Third uncertainty comes from controller (software). If the controller is not good for robot motion, the robot has a lot of error in moving. And fourth uncertainty is about hardware. For example, reliance on consumption of motor or breakdown of motor, and reliance on sensors with noise have uncertainty. In this research, we propose the way of estimation of uncertainty in robot system by use of the Bayesian Networks. Uncertainty in robot system limits robot locomotion modes. And robot can get adaptation to environmental or conditions.

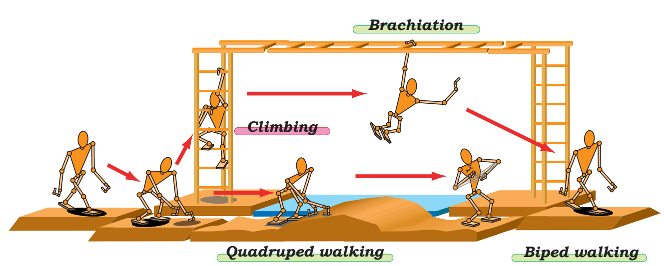

Fig. 1. Concept of Multi-Locomotion Robot

H. Sawada is with the Department of Mechanical and Science Engineering, Nagoya University, Furo-cho, Chikusa-ku, Nagoya, 464-8603, Japan sawada@robo.mein.nagoya-u.ac.jp

K. Sekiyama, T. Aoyama and T. Fukuda are with the Department of Micro-Nano Systems Engineering, Nagoya University, Furo-cho, Chikusa-ku, Nagoya, 464-8603, Japan sekiyama@mein.nagoya-u.ac.jp aoyama@robo.mein.nagoya-u.ac.jp fukuda@mein.nagoya-u.ac.jp

Y. Hasegawa is with Department of Systems and Information Engineering, University of Tsukuba, 1-1-1, Tennodai, Tsukuba, 305-8573, Japan hase@esys.tsukuba.ac.jp

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II. MULTI-LOCOMOTION ROBOT

A. Gorilla Robot III

Multi-Locomotion Robot [5] is a novel bio-inspired robot which can perform in stand-alone several kinds of locomotion such as biped walking, quadruped walking, and brachiation. We built and developed Gorilla Robot III as a prototype of Multi-Locomotion Robot. Overview and link structure of Gorilla Robot III is shown in Fig. 2. Its height is about 1.0 [m] and weight is about 24.0 [kg]. The mechanical structure is designed as follows: 6 DOF leg, 5 DOF arm, 2 DOF lumbar. Each joint is actuated by AC servo motor. Computer, AD/DA board, counter board, and power are set outside the robot.

As a sensor for recognition of slope, a laser range finder is installed at the neck of the robot (see Fig. 3). Its angular resolution is 0.36 [deg], scan angular range is 240 [deg], scan time is 100 [ms], and maximum range of detection is 4.0 [m]. The rotation axes of motors are pitch and yaw axes. In addition a web camera is also installed next to the laser range finder.

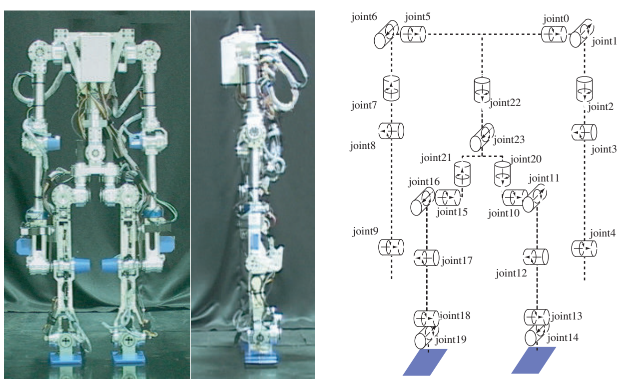

Fig. 2. Gorilla robot III

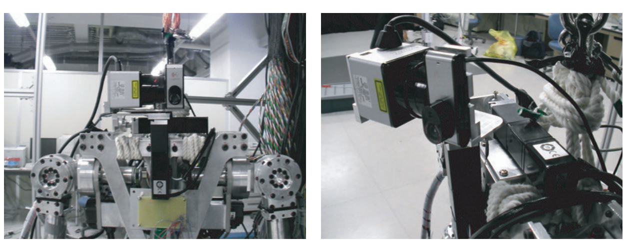

Fig. 3. Laser range finder

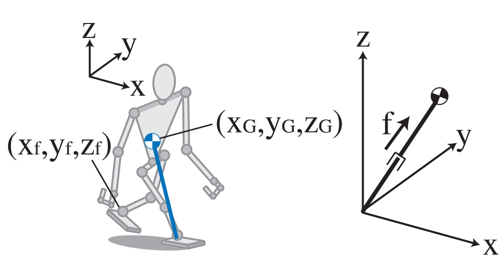

Fig. 4. Robot modeled as 3D penulum

B. Locomotion mode

In biped walk, we model the robot as a 3D inverted pendulum shown in Fig. 4, same as the work [10]. The supporting point of the pendulum is assumed to be point-contact. Then, only the heeling force f and the gravity act on Center of Gravity (COG).

In this paper, we use crawl gait as a quadruped walking [8]. In this gait, the idling leg changes, left rear leg, left front leg, right rear leg, and right front leg, in that order (see Fig. 5). It is designed in order that three feet always contact the ground, COG moves within the triangle which is formed by the three supporting feet.

The transition from biped to quadruped posture is made keeping static balance. Before transiting the posture between biped and quadruped stance, the robot stops walking.

III. LOCOMOTION STABILIZATION

In this paper, locomotion stabilization is executed along algorithm shown in Fig. 6

As prospection for locomotion, robots determine parameters about locomotion mode, walking velocity, direction or numbers of paces. This robot has biped walking and quadruped walking as locomotion mode, and on flat it travels in biped walk because flat ground is easy to walk. If on slope or rough ground it is impossible to move in biped state, robots select quadruped walking to be more robust. In this research, we propose recognition and planning using a laser range finder. A laser range finder enable robot to recognize slopes or steps. So robot modifies the position of landing or COG position adapting to environmental.

As a feedback for locomotion, this stabilization scheme has evaluation of stability based on internal condition. Robot estimates a risk of falling down using parameters which have uncertainty. If the risk of falling down is high, the robot changes walking velocity or direction, or selects internal models. But if still high, it changes locomotion modes. In this paper, we propose the method of estimating the risk of falling down using Bayesian Networks. In estimating it, we set “Robot Model Reliability (Reliability of Internal states)” and “Environmental Model Reliability (Reliability of External dynamics)”. Reliability of a robot model shows

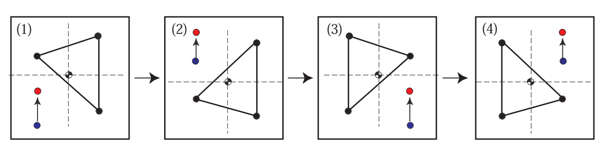

Fig. 5. Crawl gait

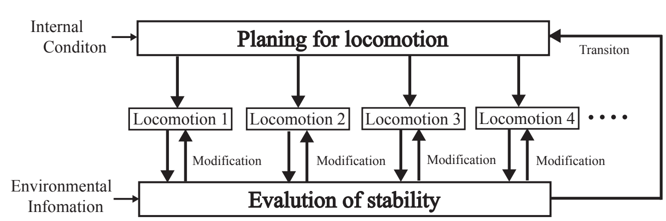

Fig. 6. Locomotion Stabilization Scheme

how far difference between reality motion and locomotion algorithm is, or physical abilities of robot. For example, if the robot has motor trouble, this is low and the risk of falling down is high. Reliability of an environmental model shows how accurately a robot recognizes environment. If robots move in dark, it does not get information of environment, so this parameter is low and the risk of falling down is high. In biped and quadruped walking, the robot evaluates both reliabilities, estimate the risk of falling down and attain an optimum gait adapting to the environments or the conditions.

IV. STABILIZATION BASED ON EXERNAL INFOMATION

A. Recognition of ground

We propose the way of calculating a gradient of ground which the robot directs to, and the boundary between two planes (between a flat and a slope, a flat and a wall) using the laser range finder. The gradient and the boundary determine how the robot transfers from a start to a goal. Fig. 7 and Fig. 8 are schematic showings that the robot measures an unknown ground. The laser runs in parallel with the sagittal plane. And the neck motor rotates around yaw axes, so the robot can acquires infomation about 3D surface. Therefore, we define the system of Cartesian coordinates so that their origin is located at the point directly under the laser range finder and design a method to recognize a landform in the x-y-z 3D space. The robot need to get (x_i, y_i, z_i) to estimate the landform. In Fig. 7, α_i is the angle of laser i to the downward direction, and di is the distance between the center of the laser range finder and the point on the ground surface. These data are obtained from the laser range finder. In addition, h is the height of the laser range finder. Then, a point on the ground surface can be described as (s_i, z_i). x_i and y_i are caluculated from s_i using the angle ofthe neck motor, β (Fig. 8). β varies from -20[deg] to 20[deg] arranged to 5[deg].

$$\begin{cases} x_i = s_i cos\beta \\ y_i = s_i sin\beta \end{cases} \quad , \quad i = 1, 2, \cdots, m \quad . \tag{1}$$

The equation of the ground surface is extracted by least-square method as $z = ax + by + c$. a, b, and c are fixed numbers. Then, the robot modifies the position of landing and the COG trajectory with this equation [11].

$$\begin{cases} s_i = d_i sin\alpha_i \\ z_i = h - d_i cos\alpha_i \end{cases} \quad , \quad i = 1, 2, \cdots, m \quad . \tag{2}$$

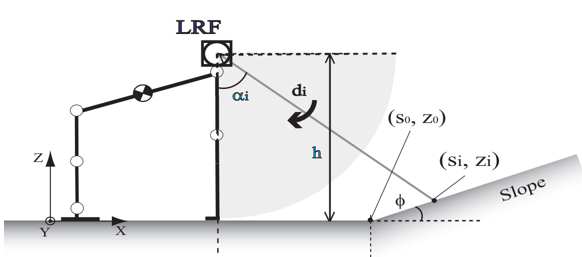

Fig. 7. Measuring slope 1

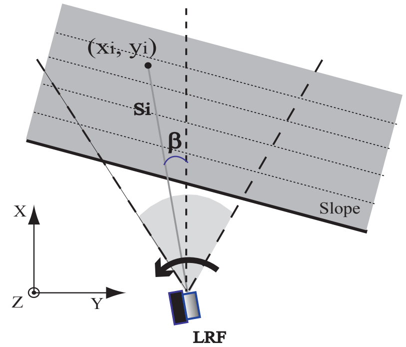

Fig. 8. Measuring slope 2

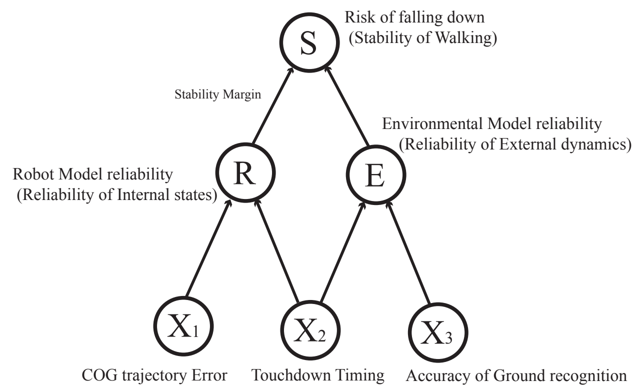

Fig. 9. Bayesian Network for locomotion Stabilization

V. STABILIZATION BASED ON INTERNAL CONDITIONS

A. Estimation of Probability

The uncertainty shown in INTRODUCTION is involved in robot's stability of walking. In this research, uncertainty in locomotion motion is dealt with to evaluate the stability. There are many kinds of uncertain parameters which have various dimensions, so it is difficult to deal with them uniformly. Then, these parameters are integrated into the risk of falling down as belief with Bayesian Network. The Bayes theory assumes that parameters have distributions individually, and posterior probability is induced formally by conditional probability. Bayesian Network is the model which describes relations among phenomenon using probability. We describe the causality between the risk of falling down and the uncertain parameters.

In this research, Bayesian Network shown in Fig. 9 is used to estimate the risk of falling down. First, Bayesian Network estimates Robot Model Reliability "R" and Environmental Model Reliability "E". Reliability of a Robot Model R show how ideal the robot motion is, and describes the capacity of moving. Reliability of a Environmental Model E is a index which shows how correctly the robot perceive the dynamics between the environment and the robot. Secondly, R and E are induced the risk of falling down "S". "$S = 1$" shows falling down, and "$S = 0$" shows not falling down. Probability variables R and E have classes 0, 1, 2 in more reliable order. Then conditional probability $P(S \mid R, E)$ reflects the performance of the robot, and the designer arranges this probability subjectively. The evaluating parameters X_1, X_2, X_3 shown below are observed at real time. Then probability variables from 0 to 4 based on uncertainty which the parameters have input the Bayesian Network. When the probability variable is 0, the situation is most stabile. The calculation of Bayesian Network uses the enumeration method shown by (3).

$$P(S=1) = \frac{\sum_{R=0}^{2}\sum_{E=0}^{2} P(S=1,R,E)}{\sum_{S=0}^{1}\sum_{R=0}^{2}\sum_{E=0}^{2} P(S,R,E)}$$

$$= \frac{\sum_{R=0}^{2}\sum_{E=0}^{2} P(S=1 \mid R,E)P(R \mid X_1,X_2)P(E \mid X_2,X_3)}{\sum_{S=0}^{1}\sum_{R=0}^{2}\sum_{E=0}^{2} P(S \mid R,E)P(R \mid X_1,X_2)P(E \mid X_2,X_3)} \quad (3)$$

The evaluating parameters X_1, X_2, X_3 are always observed, so each probability $P(X_1), P(X_2), P(X_3)$ is set 1.

1) COG trajectory Error X_1: The position of the center of gravity is measured by the force sensor which the robot put on its four legs. In biped posture, outputs which come from the sixth axis force sensor makes ZMP. In quadruped posture, the center of gravity is calculated with the equilibrium of moments. Then the errors between the desired trajectory and the observed trajectory decides the probability variable X_1.

2) Touchdown Timing X_2: The touchdown timing shows differences between the landing and the ground surface actually. When the robot is thrown off balance, or when the recognition is inadequate and the ground is higher than measured point, then the touchdown timing is earlier than the planed timing. In the robot moving, the probability variable X_2 is renewed at every landing.

3) Accuracy of Ground Recognition X_3: This parameter evaluates the performance of the recognition which the robot has. This shows how much information the robot attain with some sensors, and how abstracted the environmental model which the robot has is. The laser range finder has effective ranges, so over this ranges there is much uncertainty. Then the two-dimension recognition and the approximate algorithm have the uncertainty.

B. Consideration of Stability Margin

The conditional probability $P(S \mid R,E)$ describes the influence which Reliability of a Robot Model R have with the Risk of falling down S. Then when the stability margin is enough large compared with the COG errors, the influence is little even if R goes down. In reverse, when the stability margin is small, R has a big influence on S. Therefore $P(S \mid R,E)$ is decided based on the stability margin. For example, a stability margin in biped posture is smaller than one in quadruped posture, so $P(S \mid R,E)$ in biped posture is bigger than in quadruped posture.

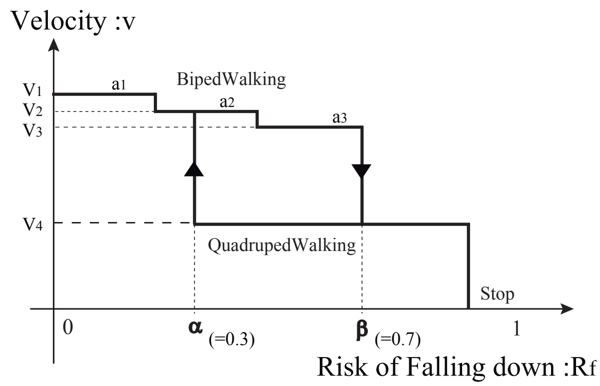

Fig. 10. Velocity - Risk of falling down

C. Shift of Locomotion Mode

The evaluating parameters X_1, X_2, X_3 are observed at real time, and the probability of falling down is estimated. The conditional probabilities used in Bayesian Network are arranged by the subjective judgments of the designer. Therefore, when the robot falls down, the probability of falling down is not always 1.0. So we pay an attention to the fluctuation of the probability. That is, when the robot move in biped posture and the risk of falling down increases, then it has the transition motion from biped to quadruped posture and go quadruped walking. Contrarily the risk decreases in quadruped walking, the robot stands up and go biped walking.

VI. Experiments

A. Experimental Conditions

In this experiment, the robot measures the landform with The laser range finder at starting point, and in walking, it get the gait based on the risk of falling down estimated by Bayesian Network shown in Fig. 10. When the risk is more than β (0.7) in biped posture, the robot squats to get quadruped posture. And when the risk is less than α (0.3) in quadruped posture, it standups. Then the robot in biped posture has three patterns of biped walking a_1, a_2, a_3 which have different efficiency. If the risk decreases, the robot get more efficient gait. In this research, this efficiency is the walking velocity, then a_1, a_2, a_3 are respectively 8.67, 6.67, 4.67[cm/sec] acquired by stride widths changed and the quadruped walking velocity is 3.00[cm/sec]. Both the standup motion and the squat motion take 10[sec] to action. Modifications of its gait are conducted in every walking cycle. The robot aims at minimizing the risk and maximizeing the efficiency all the time.

B. Experimental Result

By three experiments, we show the effectiveness of proposed method.

1) Experiment 1 (Planning based on Recognition): In this experiment, the robot walks from flat to upslope. This slope is 15[deg] and impossible for the robot to walk in biped posture. At first, it estimates the slope information in biped posture at the starting point. Based on it, the numbers of steps in biped walking are decided. Then, the robot starts biped walk and stops it at described steps to transit to quadruped posture. Finally the robot climbs up the upslope in quadruped posture. Fig. 11 is the slope information acquired by the laser range finder. The gradient error is 1.5[deg]. Snapshots of Experiment 1 are shown in Fig. 12.

2) Experiment 2 (Transition based on Risk): In experiment 2, the robot walks in biped posture on flat. Fig. 13 is the risk of falling down. The biped action a_1, a_2 or a_3 is selected by the average of the risk during one period (1.5[sec]) in every step. We can confirm a_1, a_2 or a_3 is adjusted by the risk.

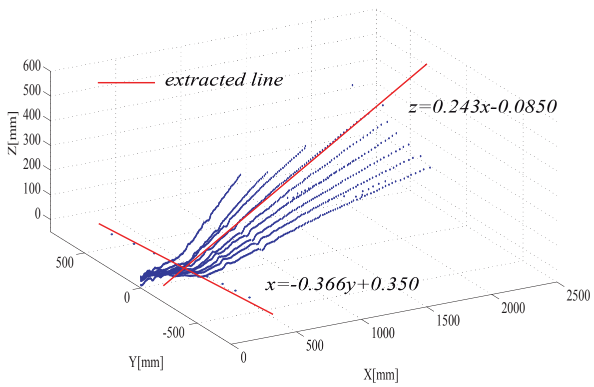

Fig. 11. Data for Recognition of slope

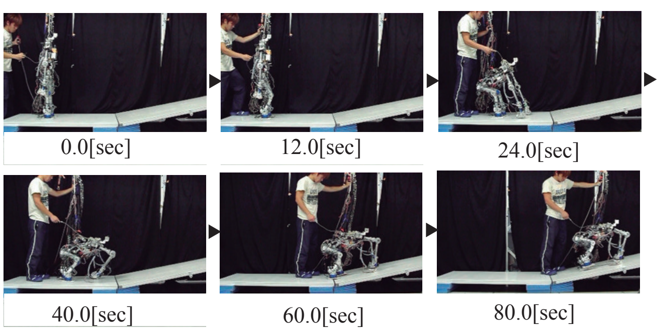

Fig. 12. Snapshots of Experiment 1

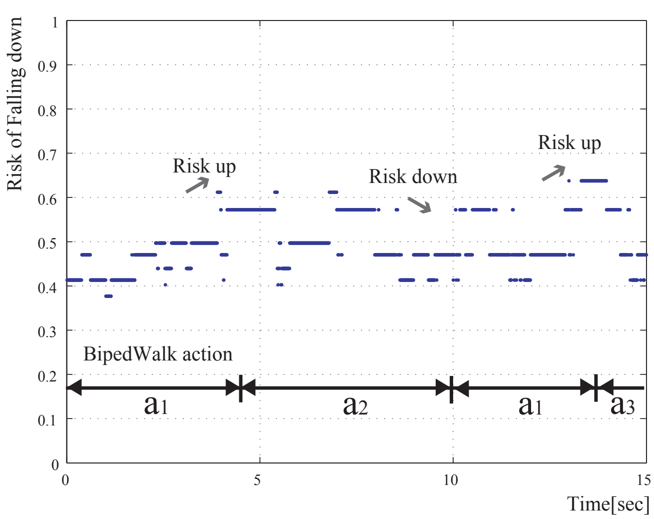

Fig. 13. Risk of Falling down 1

3) Experiment 3 (Transition based on Risk): In this experiment, the robot walks on rough ground. There are inequalities which have the maximum height, 5[mm]. This is not recognized by the robot on purpose. We confirmed whether the robot in biped posture changes the gait to quadruped mode because the risk increases.

Fig. 14 shows results about the COG trajectories come from the force sensors. And the COG trajectories induce X_1 shown in Fig. 15. Fig. 16 describes the probability variable X_2. The numbers in these figures are the threshold to apportion the probability variable. In this experiment the node X_1, X_2 have 0, 1, 2, 3, 4 as the probability variables. When the probability variable is 4, the robot almost falls down. The node X_3 is always 0 because the robot move within the effective ranges of the laser range finder in this experiment. Thus Fig. 17 is the risk estimated by Bayesian Network. In the transition motion, the risk is 0.0. We can see the transition caused by the risk increasing. Before the robot conducts a squat, the risk is more than β (0.7). And snapshots of Experiment 3 are shown in Fig. 18.

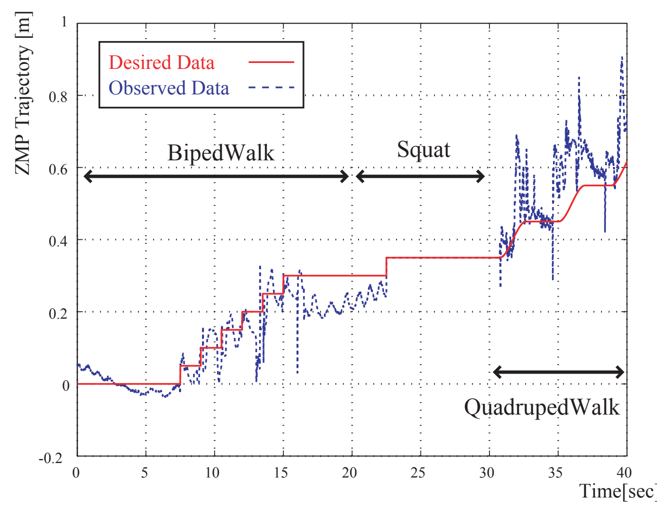

Fig. 14. Comparison between desired and actual COG trajectory

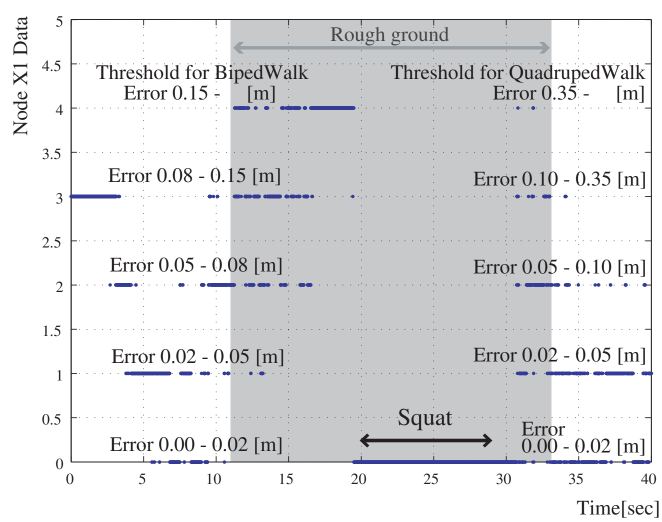

Fig. 15. Experimental Data of node X1

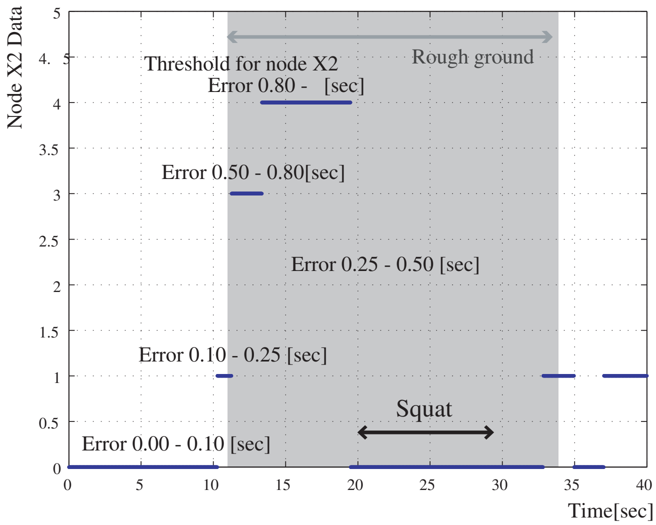

Fig. 16. Experimental Data of node X2

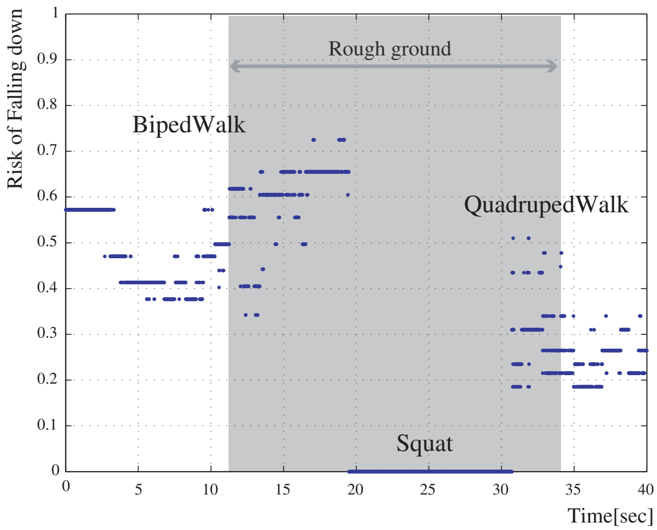

Fig. 17. Risk of Falling down 2

VII. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this paper, we made following two propositions. The first one was a method to recognize an unknown test course with the laser range finder and to plan for locomotion. The second one was the way of estimating the uncertainty as the risk of falling down. And the robot decides its gait based on the recognition and the risk. By experiments, we verified the proposed methods can be applied to various cases, and showed that stable locomotion with transition between biped and quadruped walk have been realized.

B. Future Works

Although we dealt with only biped walk and quadruped walk in this paper, we will deal with other locomotion modes such as brachation and ladder climbing for transition. Furthermore, we will add the Bayesian Network for the risk of falling down to more parameters, and diagnose the causes which give the robot system the uncertainty mainly.

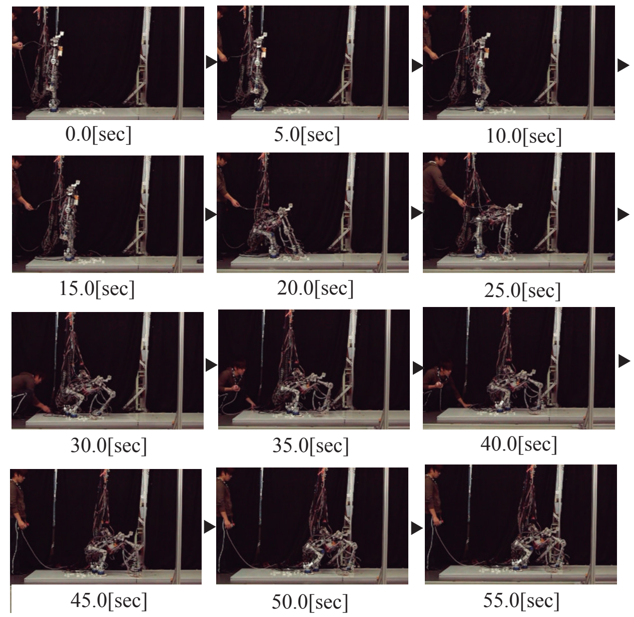

Fig. 18. Snapshots of Experiment 3

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