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Robotics and Autonomous Systems 54 (2006) 631–640

Robotics and Autonomous Systems

www.elsevier.com/locate/robot

Sensing through body dynamics

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Received 17 October 2005; received in revised form 5 March 2006; accepted 7 March 2006
Available online 19 June 2006

Abstract

It has been shown that sensory morphology and sensory–motor coordination enhance the capabilities of sensing in robotic systems. The tasks of categorization and category learning, for example, can be significantly simplified by exploiting the morphological constraints, sensory–motor couplings and the interaction with the environment. This paper argues that, in the context of sensory–motor control, it is essential to consider body dynamics derived from morphological properties and the interaction with the environment in order to gain additional insight into the underlying mechanisms of sensory–motor coordination, and more generally the nature of perception. A locomotion model of a four-legged robot is used for the case studies in both simulation and real world. The locomotion model demonstrates how attractor states derived from body dynamics influence the sensory information, which can then be used for the recognition of stable behavioral patterns and of physical properties in the environment. A comprehensive analysis of behavior and sensory information leads to a deeper understanding of the underlying mechanisms by which body dynamics can be exploited for category learning of autonomous robotic systems.

Keywords: Legged locomotion; Passive dynamics; Object recognition; Categorization

1. Introduction

While design principles of traditional robotic systems assume rigid body materials and high-gain control, there has been an increasing interest in broader ranges of material properties and adaptive control. In particular, the use of passive dynamics for behavior control has provided a significant conceptual impact. One of the most fundamental aspects of passive dynamics, or more generally body dynamics, lies in the fact that behaviors and functions should be viewed as a result of the interplay between morphological properties, control and environment. The studies of passive dynamic walkers and rapid legged locomotion have nicely demonstrated how morphological properties are related to the behavior of the system. When a system exploits morphological properties (e.g. shape, stiffness, friction, weight distribution), it is possible to simplify the control architecture and to achieve energy-efficient behavior. Even without any actuation, for example, passive dynamic walkers are able to walk down a slope in a very natural way [1,2], and they require extremely small amounts of energy for walking even on level ground [3,4]. For energy-efficient rapid locomotion, in addition, the use of elastic materials has been successfully applied in the legged robots [5–7].

A common characteristic of these robots is that their behaviors are intrinsically dependent on the physical properties of the environment. For example, passive dynamic walkers can function only in very limited environmental conditions, i.e. a slope with a specific angle and a limited range of ground friction. If the angle of the slope is varied slightly, the passive dynamic walker is no longer functional and falls over. In order to deal with complex passive dynamics in the real world, it can be concluded that the control system has to be adaptive and dynamic [8–11].

Dynamic system–environment interactions are important not only for energy-efficient adaptive behavior but also for sensing. When sensor morphology and sensor–motor coupling are exploited, a system is able to obtain "structured" sensory information about the physical properties of the environment [15]. The concept of sensory–motor coordination is, in essence, that the constraints of robotic systems derived from sensory morphology and mobility can be exploited for simplifying the processes of object recognition [14] and category learning [16,17] as well as controlling behaviors in

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0921-8890/$ - see front matter
doi:10.1016/j.robot.2006.03.005

general. Although these studies of sensory–motor coordination in robotics implicitly assumed rigid body structures and high-gain control, some of the biological models in neuroscience take body dynamics into account. In particular, the so-called "forward models" are of particular interest because they imply the fact that animals actually deal with body dynamics in their sensory–motor control: these models explain the fact that, rather than directly connecting sensors and motors, biological systems use the learning functions for complex motor control of body dynamics (for reviews, see [12,13]). In robotics, the use of body dynamics for sensing has not been explicitly explored so far. For example, by using robots with elastic fingers, feet, or whiskers (made of different kinds of material), it was shown that dynamic properties of morphology and materials significantly influence the identification processes of the environments [18–20].

This paper explores design principles of the whole body dynamics for the purpose of sensing. By analyzing the interaction between passive dynamics, motor control, and the environment, we investigate the roles of the body dynamics in the generation of information structures in the sensory input. First, we describe a four-legged robot model tested in both simulation and the real world. The case studies show how attractor states of the robot's locomotion behavior generated by the intrinsic stability are related to the information structures in the sensory stimulation. Secondly, we show how these structures in the sensory information can simplify the identification of stable behavioral patterns, and the recognition of physical properties in the environment. The analysis of low-level motor control and sensory information also provides an additional insight into the underlying mechanisms by which body dynamics can be exploited for category learning of adaptive autonomous robots.

2. Body dynamics of a quadruped robot

The use of elastic muscle–tendon systems during rapid locomotion has been investigated in biomechanics, which leads to the theoretical model of legged animals, the so-called "spring–mass model" [24–28]. In this model, it was hypothesized that an animal's leg could be approximated by a spring-loaded inverted pendulum. The studies of the spring–mass locomotion models have shown that, with a proper implementation of the self-stabilization mechanisms, many aspects of rapid legged locomotion can be passive or they require extremely simple control (e.g. [29,30]). In this section, we introduce how stable locomotion behavior can be achieved by a minimalistic control architecture in a four-legged robotic platform [21,22].

2.1. Morphological design

The design of the robot is inspired by the spring–mass model studied in biomechanics. As shown in Fig. 1, the robot has four identical legs, each of which consists of one standard servomotor (KOPROPO PDS947FET) and a series of two segments connected through a passive elastic joint. We used

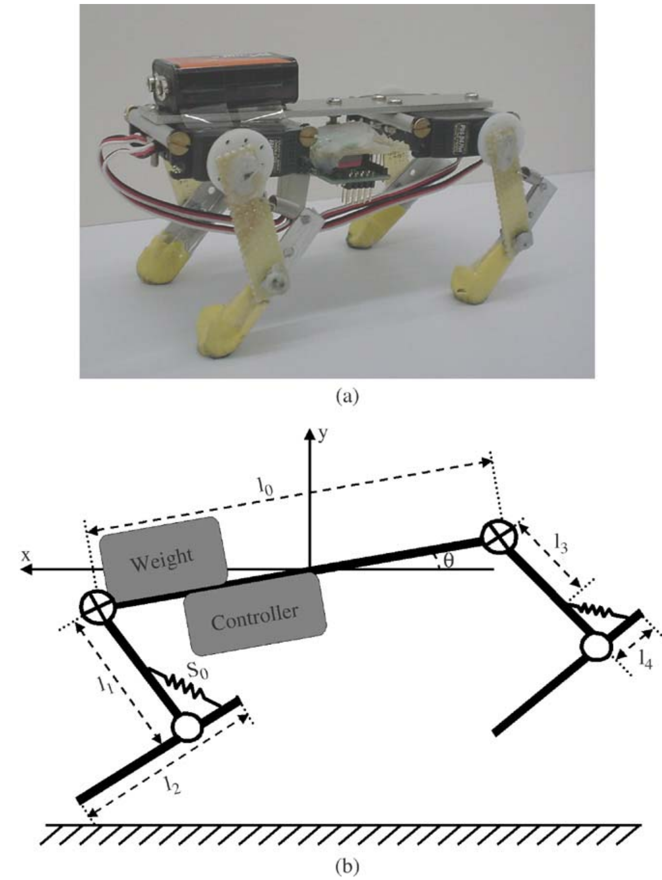

Fig. 1. Four-legged robot used in the experiments: (a) a photograph and (b) a schematic. The circles denote passive joints and the circles with a cross inside denote the joints controlled by the servomotors. The specifications of the robot are shown in Table 1.

Table 1
Specification of the robot platform

Parameters	Description	Value
l_0	Length of body	142 mm
l_1	Length of upper leg limb	42 mm
l_2	Length of lower leg limb	56 mm
l_3	Spring attachment	15 mm
l_4	Spring attachment	20 mm
s_0	Spring constant	40 g/mm
m	Mass of the robot	473 g

aluminum for the design of body frame and legs. The physical dimensions of the robot body are 142 mm long, 85 mm wide and approximately 75 mm high (refer to Table 1 for more detailed specifications). The robot has four servomotors, a micro-controller (Microchip PIC 16F877) and a small weight to adjust the weight distribution of the body, which result in a total weight of 473 g. The control signal for the motors and the electricity are supplied externally through the cables. We used the standard serial communication protocol to send the positions of the servomotors from a PC to the micro-controller that produces the modulated signals for the servomotors.

To gain a higher forward velocity, the robot requires higher ground friction. For this reason we implemented a rubber surface at the ground contact in each leg. Although it is difficult to quantitatively measure the ground friction during dynamic interaction between legs and ground, a good estimate is the coefficient of friction. The static and dynamic coefficients of friction are approximately 0.73 and 0.55, respectively.

2.2. Motor control

In order to understand the intrinsic body dynamics derived from the morphological properties, we apply a minimalistic control strategy, in which no sensory feedback is used at the level of global function. In the following experiments, the motors are controlled by a simple oscillatory position control as follows:

$$P_f(t) = A_f \sin(\omega t) + B_f \quad (1)$$

$$P_h(t) = A_h \sin(\omega t + \phi) + B_h \quad (2)$$

where P_f and P_h indicate the target angular positions of the fore (shoulder) and hind (hip) motors, respectively. A and B designate the amplitudes and the set points of the oscillation, and the frequency ω and the phase ϕ the phase delay between the fore and hind legs. Control of the motors is symmetric in terms of the sagittal plane, i.e. the control of two fore legs is the same. The parameters used in the following experiments are heuristically determined as follows: $A_f = A_h = 25$ (degrees), $B_f = 20$ (degrees), and $B_h = 10$ (degrees). The control parameters of frequency ω and phase ϕ will be used for the parameter search.

2.3. Intrinsic stability

Although most of the compliant legged robots use sensory information to achieve stable rapid locomotion (e.g. [30–32]), this locomotion model does not: the controller does not need to distinguish stance and swing phases of the legs, the body attitude or leg angles with respect to the absolute ground plane, but stable locomotion behavior can be achieved by a self-stabilization mechanism exploiting the compliant legs (Fig. 2, [21,22]). In the first set of experiment, we analyze the stability of the locomotion method without sensory feedback. Fig. 3 illustrates typical time-series state variables which characterize the movement of the robot body during one leg cycle. For this analysis, the locomotion behavior was recorded by a high-speed camera (Basler A602fc, 100 fps), and two tracking points of the robot body were extracted by a standard visual tracking method, with which its movement can be identified. As shown in this figure, all five state variables (i.e. $\dot{x}$, y, $\dot{y}$, θ, and $\dot{\theta}$) go back to the states at the beginning of the leg step cycle, which ensures the periodic gait pattern.

By searching through the control parameters, we observed at least two qualitatively different gaits which are labeled "Gait 0" and "Gait 1", as shown in Fig. 2. In Gait 0, the hopping height is larger than in Gait 1, which results in the four legs being clearly off the ground for some duration in a leg cycle. Gait 1 generally exhibits larger forward velocity. The intrinsic stability of the locomotion method can be demonstrated by switching between the control parameters of these gaits. A typical response induced by the change of the gait is shown in Fig. 4 (the control parameter of phase ϕ is varied at time $t = 0$). Generally the stable gait patterns can recover within one or two leg steps after the switching of the control parameters.

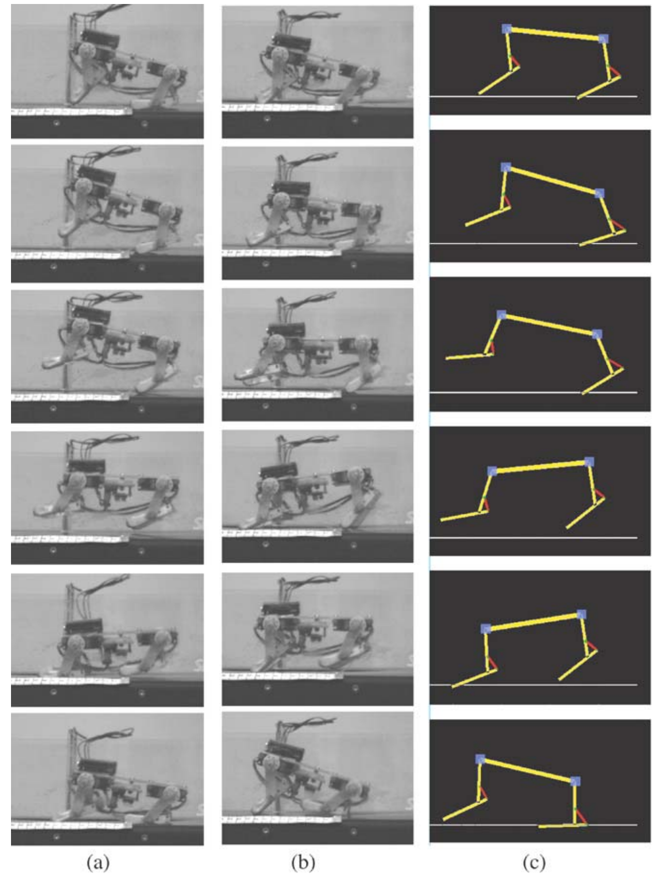

Fig. 2. Illustration of the behavior of the real and simulated robot. Time-series photographs during (a) "Gait 0" (frequency = 3.2 Hz, phase = 0 rad) and (b) "Gait 1" (frequency = 4 Hz, phase = 0.5 rad). The behavior of the robot is visually registered while running on a treadmill. The interval between two pictures is approximately 30 ms. (c) Behavior of simulation model.

In general, there exist multiple stable gait patterns in this framework of quadrupedal locomotion, and the number largely depends on the ground friction. However, even during the unstable locomotion, it does not fall over but maintains the locomotion process.

2.4. Simulation model

In order to complete our comprehensive behavior analysis, we have constructed a simulation model of the running quadruped robot. The simulation was conducted in Mathworks Matlab 7.01 together with the SimMechanics toolbox. We developed this model to reflect the essential characteristics of the real robot in a planar environment. It consists of 5 body segments (a pair of two-segment legs and a body segment), two linear springs, and two motors in shoulder and hip joints with angular position feedback (for simulating the servomotors). We made use of a ground friction model which is well studied in biomechanics [23]. As a result, the simulated dynamic locomotion is fairly comparable to the real one, as shown in

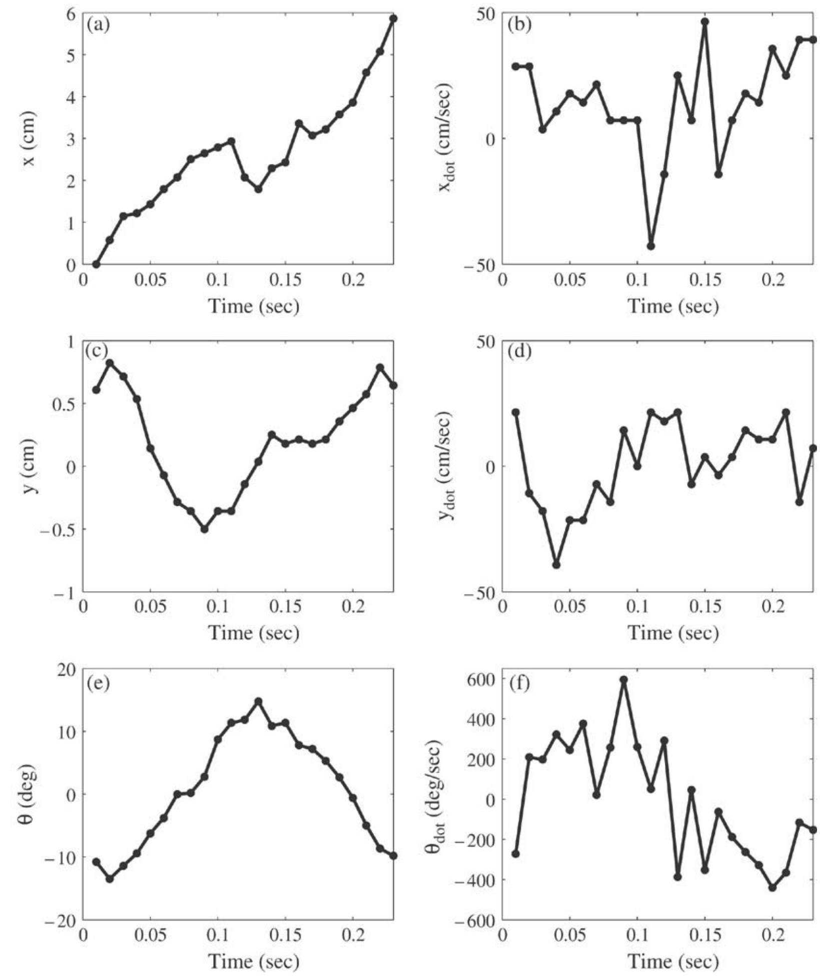

Fig. 3. Time-series changes of the state variables during one leg step cycle, (a) horizontal, (c) vertical, (e) angular movement and their velocity (b), (d), (f).

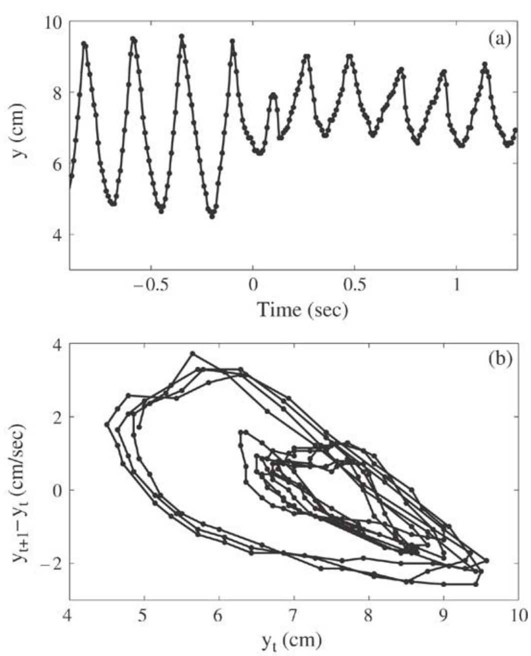

Fig. 4. A typical recovery response from the change of the gait. (a) The time-series of the vertical movement of the body is shown before and after changing the frequency parameter at time = 0, and (b) its phase plane trajectory.

Fig. 2. The following experimental results are obtained by using this simulation model.

3. Behavior and sensory information

Sensory information acquired during the locomotion process is explored in this section. We conducted three simulation experiments to characterize the relation between locomotion behavior, control and the sensory information.

By tuning the control parameters, stable running behavior of the simulated robot could be achieved, as shown in Fig. 5(a). During this locomotion process, we registered the time-series response of several different sensory channels, i.e. a pressure sensor on the sole of hind leg, an angle sensor of the hind passive joint, an inertia sensor in the body segment, and a motor torque sensor in the hip joint. As shown in Fig. 6(a), all of the sensory signals show a periodic response due to the stable locomotion behavior.

In the second experiment, the coefficient of ground friction is varied, which results in unstable locomotion behavior with the same control parameters. Fig. 5(b) illustrates a typical unstable behavior of the system: some periodic patterns are disappearing after a few leg steps due to accumulation of small slippage and undesired touch-down angles of the legs. Consequently, the sensory response also shows unstable patterns (Fig. 6(b)):

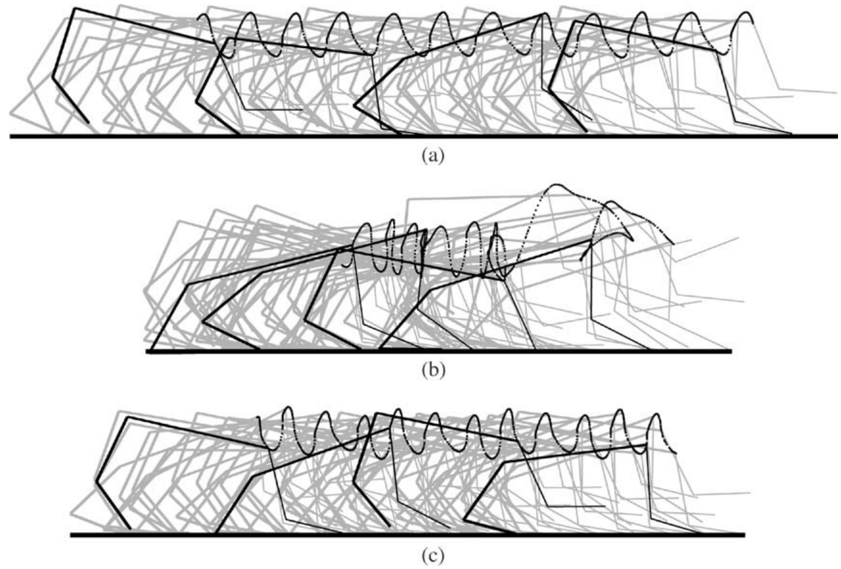

Fig. 5. Stick figures illustrating three different behaviors in simulation. The body postures are illustrated every 100 and 1000 simulation steps (gray and black stick figures, respectively). Black dots represent the trajectories of the shoulder joint. (a) $\omega = 4.7$ Hz, $\phi = 0.3$ in the ground friction 0.9 (static) and 0.8 (dynamic). (b) The same control parameters in the ground friction 0.7 (static) and 0.6 (dynamic). (c) In the same ground friction as (b) with the control parameters $\omega = 4.9$ Hz, $\phi = 0.4$.

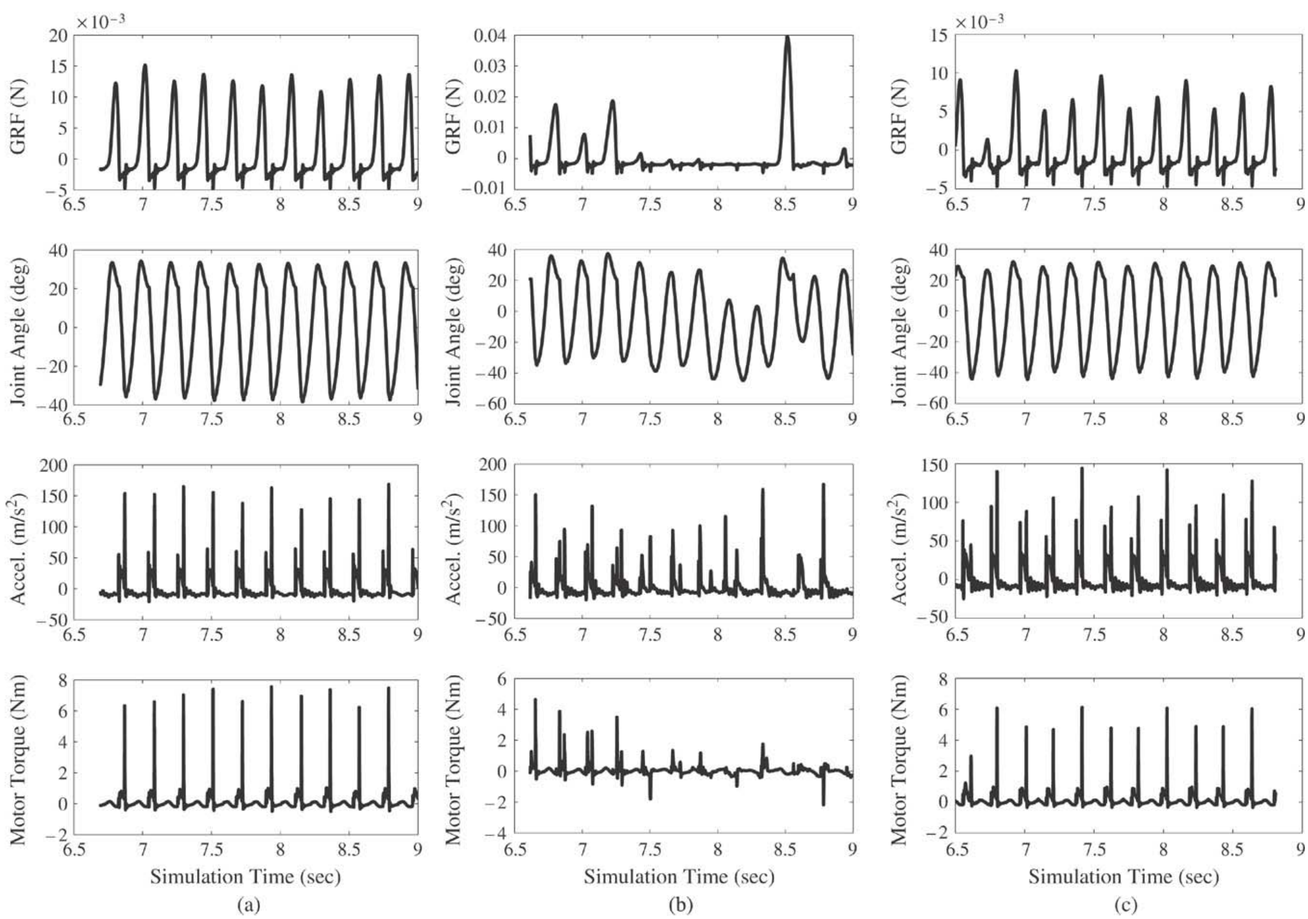

Fig. 6. Sensory information acquired during the behaviors shown in Fig. 5. From top figure to bottom: pressure sensor in the hind leg, angle of the hind passive joint, acceleration of the body, and motor output torque of the hind leg. (See the text for more details.)

the ground reaction force and the motor torque in particular are substantially different compared to Fig. 6(a).

In the third set of experiments, the control parameters are adjusted for stable locomotion behavior in a different environment. Although this locomotion exhibits slightly slower forward speed and larger hopping height, it is possible to achieve comparable stability to that of the first experiment (Fig. 5(c)). The sensory information also shows stable periodic patterns very similar to the first ones (Fig. 6(c)).

There are two implications from these experimental results. Firstly, the magnitude of the ground friction is reflected in four sensory channels (i.e. foot pressure, joint angle, acceleration, and motor torque sensors). This is possible because the intrinsic stability of the locomotion process is achieved through the body dynamics: the dynamic locomotion process results from a number of different physical interactions, and the different physical properties of the environment influence these interactions. In this case study, for example, there are, at least, the ground reaction force exerted at the feet, the force generated in the elastic passive joints, the output torque of actuators, and the momentum of the large masses in the body.

Secondly, the relation between control parameters and sensory stimulation has to be considered further. Assuming that a sensory–motor control maintains a stable locomotion process, the sensory stimulation of the four sensory channels in different environments would not be significantly different: in the third experiment, because the control parameters are adjusted for the different environment, the sensory patterns of the first and the third experiments (Fig. 6(a) and (c)) are difficult to distinguish. From this example, it can be concluded that the sensory stimulation has to be considered in relation to body dynamics and sensory–motor coordination. This point will be discussed further in Section 6.

4. Sensing body dynamics

In the following experiments, we investigate the influence of frequency ω and phase ϕ on the locomotion behavior. These parameters significantly change the locomotion behavior; the robot exhibits a stable rapid locomotion; it runs slowly or hops in place; it exhibits unstable behavior; or it falls over.

This dynamic locomotion behavior can be identified in a relatively simple manner by analyzing temporal patterns of the sensory signals. We implemented two sensors in the simulation model, i.e. a ground contact detector in the fore foot and a speed detector at the body segment. First, a ground contact detector (an on-off mechanical switch in the fore foot) is tested. By measuring the duration of a swing phase (i.e. the duration of the leg in the air), the stability of the locomotion behavior can be estimated. In Fig. 7, the duration of the swing phase during the 10 s of experiment is plotted against the phase parameter ϕ. This figure shows that the stability of the locomotion can be identified by measuring the duration. For instance, with the phase parameter around 1.0 rad, the duration is relatively constant at approximately 0.1 s, which indicates that the locomotion behavior is periodic. By contrast, the locomotion with values ϕ between -1.5 and 0.5 shows a large variance, which can be interpreted as the locomotion being rather unstable. The stability of locomotion is more clearly shown by calculating the standard deviation (SD) (Fig. 7(b)): the lower the value of SD, the more stable locomotion. Note

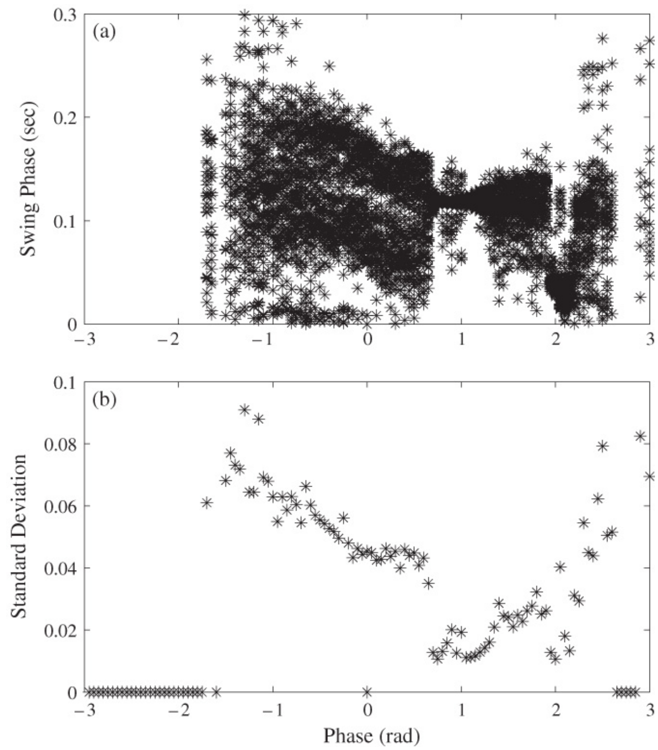

Fig. 7. Body dynamics during the locomotion experiment measured by a contact detector. (a) Distribution of the flight phase durations against the phase parameter, and (b) its standard deviation.

that the plots of SD $= 0.0$ indicate that the robot could not successfully finish 10 s locomotion experiment, but it fell over (e.g. $-3 < \phi < -1.8$).

In a similar way, we have conducted simulation experiments by changing both parameters of frequency and phase. Fig. 8(a-0) shows the distribution of SD. From this figure, we could see how periodic the sensory information is for each set of control parameters. In the remainder of this paper, we call this two-dimensional diagram the "behavior landscape". The range of the frequency parameter is set to 3–5 Hz, reflecting the constraints from the hardware.

Now we introduce another sensory channel which measures the average forward speed of locomotion. (We assume that the robot has a vision sensor which measures the optic flow, for example.) The average forward speed also contains temporal information which indicates the characteristics of locomotion behavior. For example, the average forward speed is generally faster when the locomotion behavior is periodic. Fig. 8(b-0) shows the behavior landscape in terms of the average forward speed. The average forward speed is obtained in the same 10 s locomotion experiments in which the SD of the swing phase was measured.

It is important to mention that there is a certain "structure" in these behavior landscapes. To make it more visible, we applied some threshold values, and the behavior landscape is redrawn with the white and black patches, as shown the Fig. 8(a-1-3) and (b-1-3). For example, figure (a-1) has a white region at the right side, which indicates "periodic" locomotion; figure (a-2) shows a large white region in the right half which corresponds

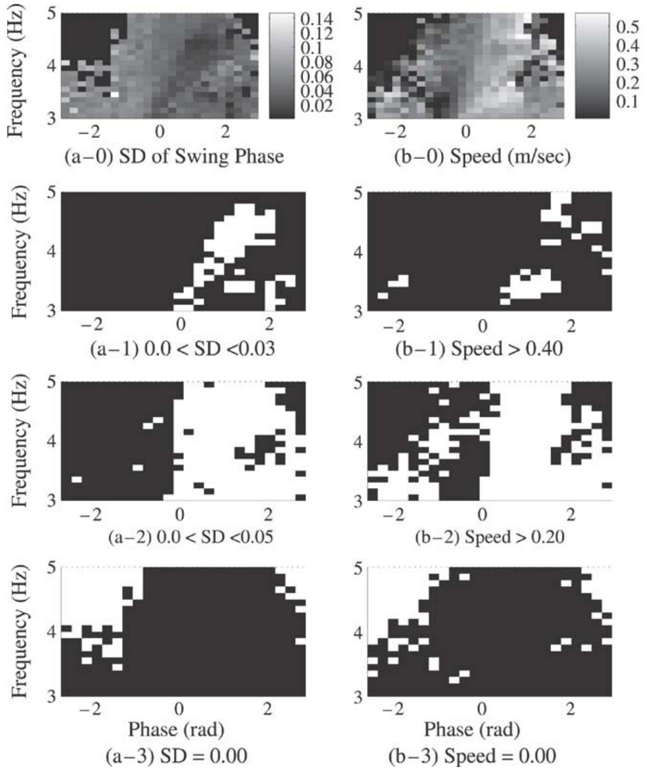

Fig. 8. Behavior landscapes from various sensors. (a-0) ground contact detector, and (b-0) speed detector. This landscape is then segmented by various thresholds (a-1-3) and (b-1-3). White and black patches denote the values above and below the thresholds.

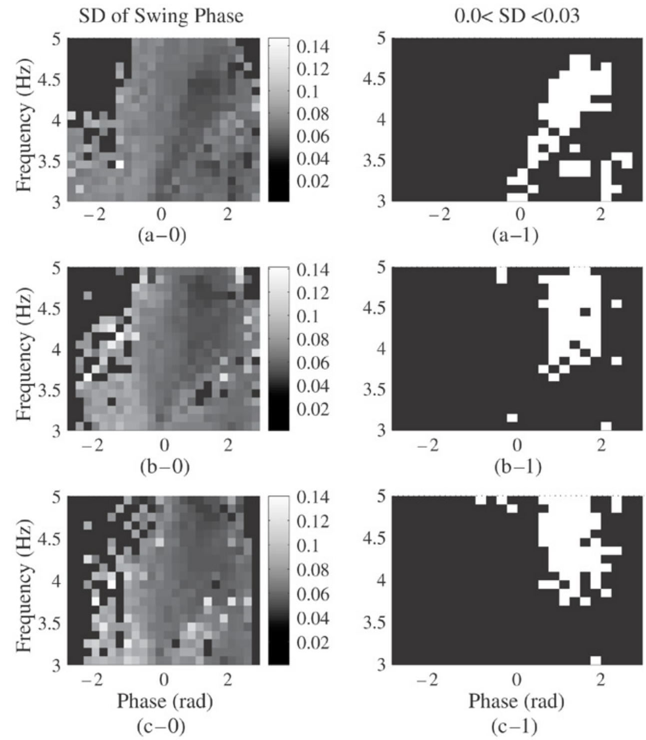

Fig. 9. The different dynamics measured by the contact detector for different body masses: (a) 0.5, (b) 1.0 and (c) 1.5 kg. The landscape is then segmented by threshold in (a,b,c-1).

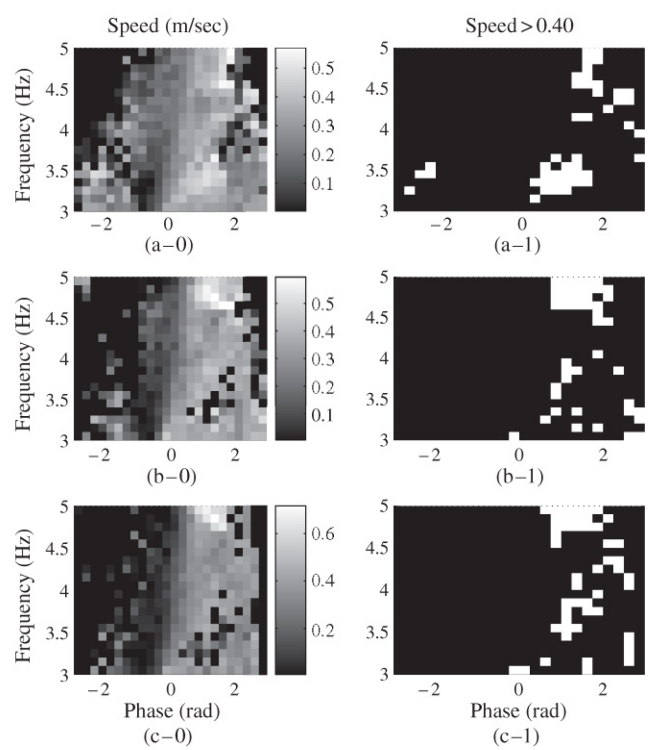

Fig. 10. The different dynamics measured by the speed detector for different body masses: (a) 0.5, (b) 1.0 and (c) 1.5 kg. The landscape is then segmented by threshold in (a,b,c-1).

to "relatively stable" locomotion; and figure (a-3) shows the regions of"unstable" locomotion. Similarly, figure (b-1) shows the regions of "fast" locomotion; (b-2) "relatively fast". Note that all these physically meaningful terms of stability and velocity (the words with double quotes) are from an observer's perspective, and the robot itself does not "know" what these values mean. However, these physically meaningful states can potentially be discretely identified due to the attractor landscape that has its origin in the body dynamics.

5. Sensing physical properties

This section explores how the measurement of body dynamics can be used for sensing. Two case studies will be introduced, in which two physical parameters were changed. In the first series of experiments, we set the body mass of the robot at three different values, and then analyze how the robot could discriminate these differences through two sensory channels. In the second series of experiments, the coefficient of friction is examined also with three different values.

5.1. *Effect of body mass*

We conducted the three simulation experiments in the same way as described in the previous section, but with three different body mass of 0.5, 1.0 and 1.5 kg by increasing the weight of the body segment. And again, the stability of the behavior is analyzed with respect to SD and average forward speed by varying the motor control parameters. The result obtained from the contact detector is shown in Fig. 9, and the one from the speed detector in Fig. 10. As shown in Fig. 9, the rough

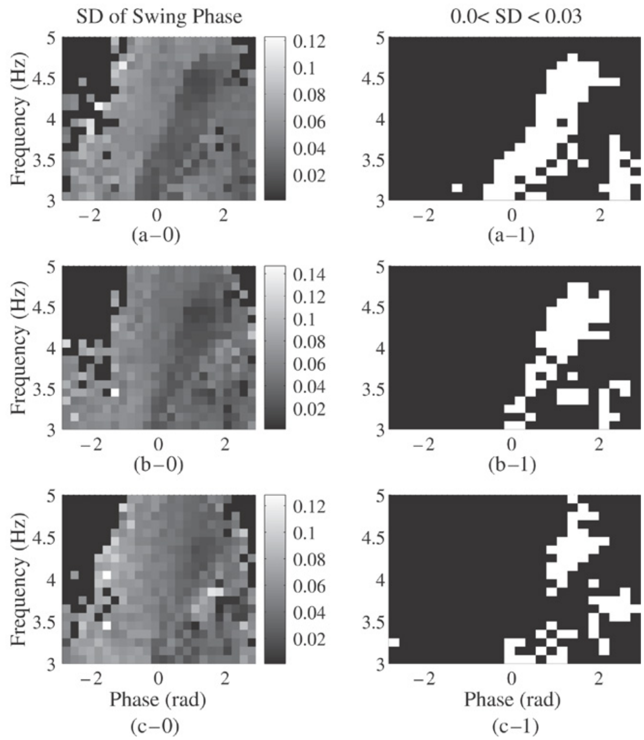

Fig. 11. The different dynamics measured by the contact detector for different ground friction: (a) 0.5, (b) 0.65 and (c) 0.8. The landscape is then segmented by threshold in (a,b,c-1).

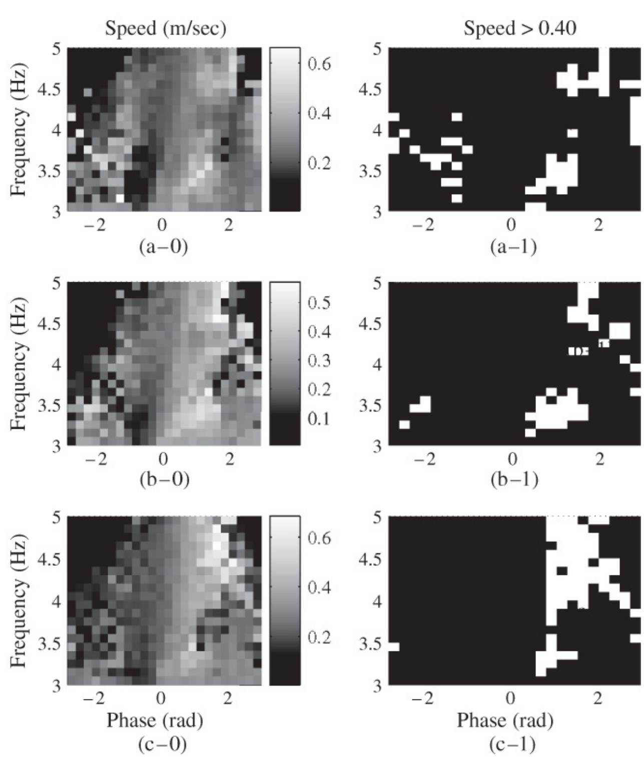

Fig. 12. The different dynamics measured by the speed detector for the different ground friction: (a) 0.5, (b) 0.65 and (c) 0.8. The landscape is then segmented by threshold in (a,b,c-1).

structures of the figures (a,b,c-0) are somewhat similar: the area of "unstable" locomotion is in the upper left corners; the area of "periodic" locomotion is at the upper right regions. To show it more clearly, we again applied a threshold value as shown in Fig. 9(a,b,c-1). (The value of the threshold has been heuristically determined.) By setting a threshold, we could see that the stable region moves toward higher frequency as the body mass increases. The average forward speed shows an even clearer tendency; with the light body mass, there are two peaks in the landscape, i.e. the regions at the lower middle and at the upper right, whereas the lower middle region disappears as the body mass increases.

An important implication from these experiments is that the difference of the body mass can be identified by using two different sensory channels, i.e. the contact detector and the vision sensor. This is because the physical differences are reflected in the dynamic behavior of the body; as a consequence the foot contact and the forward speed are physically related to the body mass. For example, with the light body weight, periodic running behavior can be inferred from the sensors at the range of middle motor frequency, whereas the sensors indicate more unstable locomotion as the weight increases.

5.2. *Effect of ground friction*

The next case study focuses on the difference in the environment, rather than the body of the robot itself. By following the same procedure as in the previous experiments, we now examine the behavior landscape with three different friction coefficients of the ground, i.e. 0.5, 0.65, and 0.8. (The body mass is set to 0.5 kg.) The distribution of SD is shown in Fig. 11 and the average forward speed in Fig. 12.

From the distribution of SD shown in Fig. 11, the difference in the ground friction can be clearly identified between (a-1) and (c-1): the white patches in the motor parameters around frequency 3.5 Hz and phase 0 degree disappear as the friction coefficient increases. For average forward speed, on the other hand, there is a large white region at the upper right with the high ground friction (Fig. 12(c-1)).

This experimental result again shows that both the contact detector and the visual sensor are able to display the difference in the ground friction. For example, when the ground friction is changed from low to high, periodic running behavior is no longer possible at the low frequency motor control, as can be detected by a contact detector and a vision sensor.

6. Discussion

Because the body dynamics of biological systems are generally controlled by sophisticated sensory–motor processes, it is often difficult to extract the underlying principles of how morphological properties of the body can be used for the purpose of sensing. However, by developing and analyzing artificial creatures as demonstrated in this paper, the design principles of morphology and body dynamics can be conceptualized for a comprehensive understanding of the perception mechanisms. Based on the experimental results of this paper, in this section, we discuss the roles of body dynamics with respect to two fundamental functions of adaptive autonomous systems, i.e. recognition and category learning of physical properties in the environment.

The relation between body dynamics and the recognition process was demonstrated in Section 3. As shown in Fig. 5(a) and (b), salient behavioral differences occur in different environments. More specifically, because the stable locomotion process results from the system–environment interaction, differences in ground friction influence the way in which the passive joints and the feet interact with the ground. These salient differences in the behaviors can be used to estimate the differences in environment by measuring its own behaviors. In this sense, morphological properties can be exploited to magnify the influence of the physical properties for the purpose of sensing. As a result, calculating standard deviations and simple thresholding can be sufficient to discriminate different environments. More precise information about the physical properties of the world can be acquired through accurate motor control and multi-modal sensory channels (see the experimental results in Section 5). For example, by comparing Fig. 11(a-1) and (b-1), the coefficients of ground friction 0.5 and 0.65 can be identified by the ground contact detector, when it runs with the control parameters of frequency 3.5 Hz and phase 0 degree: in the former case it is in the white (stable) region; in the latter in the black (unstable) region.

A problem of this recognition process is a large time delay, i.e. a few leg steps are required to identify the environment. These implications are, however, particularly interesting in the context of developmental process of autonomous systems. During a development phase with no good capability of motor control, the system is able to acquire multi-modal sensory information. For a situated system, the sensory information acquired through one sensory channel only is not very meaningful. Generally in conventional robotic systems, sensory information is interpreted by a human designer and implemented in a control program. For a system which grows through the interaction with the environment, however, it is a fundamental issue how the system interprets acquired sensory information as pointed out by the so-called "grounding problem" [33–35]. For the grounding problem, sensory information becomes more "meaningful" if it is correlated with information from other sensory modalities. Because information from each sensory channel is generated by a certain physical interaction, the robot is able to learn the relation between different physical interactions by correlating the respective information. For example, the body mass can actually be measured by a single sensory channel, a simple pressure sensor on the foot. The information extracted from this sensory channel, however, becomes more meaningful if it is combined with information from other sensory channels, e.g. locomotion speed, the force exerted on the leg joints, energy consumption, and motor signals. The robot might be able to "understand" the meaning of the slope angle or of high friction, by correlating sensory patterns from different channels, for example.

With a sensory–motor coordinated action, the salient differences in sensory information can be significantly reduced due to the stable behavioral patterns. For example, the sensory information of Fig. 6(a) and (c) is qualitatively very similar. This experimental result implies that, with a sensory–motor control which maintains a stable locomotion process, the apparent sensory input cannot always provide the information about the environment, but the motor output has to be considered as well. With similar patterns in sensory stimulation (as in Fig. 6(a) and (c)), the physical properties can be estimated from the motor output. In this sense, the sensory–motor control is an important requirement for the function of categorization. It would be interesting to investigate further how we could design body dynamics that can be used for better categorization by using motor signals.

Body dynamics becomes more important in the context of category learning. The influence of body dynamics for category learning is indirectly demonstrated in the fact that we need to search only through two-dimensional behavior landscapes for effective control parameters which generate a relatively complex running behavior of the quadruped robot. Because of the intrinsic body dynamics, there are only a few parameters that need to be explored to find particular behaviors for sensing. Although we still do not fully understand how a system can deal with the balance between rich sensory information and stable locomotion behaviors, the parameter space for the sensory–motor coordination can be significantly reduced by taking body dynamics into account.

7. Conclusion

This paper presents a few case studies demonstrating body dynamics can be exploited for sensing. By exploring a dynamic locomotion model of a four-legged robot in simulation and the real world, a number of benefits of this approach are explained in concrete terms. In particular, it is shown that, by exploiting the system–environment interaction derived from body dynamics, a number of physical properties are reflected in the multi-modal sensory information (e.g. body weight, ground friction). Although we still have to elaborate what the "good" body dynamics for sensing is, the experimental results are highly encouraging. Given the fact that all sensing in biological systems is through body dynamics, static or quasi-static sensory stimulation represents only special cases of the general phenomenon. From this perspective, we hope that the exploration of body dynamics for sensing will lead to our further understanding of the relation between body dynamics, control and sensing for the purpose of object recognition and category learning of adaptive autonomous systems.

Acknowledgement

This research is supported by the Swiss National Science Foundation (Grant No. 200021-109210/1).

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