AI in Locomotion: Challenges and Perspectives of Underactuated Robots

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Abstract. This article discusses the issues of adaptive autonomous navigation as a challenge of artificial intelligence. We argue that, in order to enhance the dexterity and adaptivity in robot navigation, we need to take into account the decentralized mechanisms which exploit physical system-environment interactions. In this paper, by introducing a few underactuated locomotion systems, we explain (1) how mechanical body structures are related to motor control in locomotion behavior, (2) how a simple computational control process can generate complex locomotion behavior, and (3) how a motor control architecture can exploit the body dynamics through a learning process. Based on the case studies, we discuss the challenges and perspectives toward a new framework of adaptive robot control.

1 Introduction

Navigation is one of the most fundamental functions of adaptive autonomous systems and it has been a central issue of artificial intelligence. As in most of the other topics of AI research, navigation has been traditionally treated as a "sense-think-act" process, where the problem is generally decomposed into three subprocesses of (1) identifying the situation, i.e. mapping the sensory stimulation on to an internal representation, the world model, (2) planning an action based on this world model, and (3) executing the physical action. In this framework, the navigation problem was nicely formulated by engineering terms as exemplified by the Simultaneous Localization and Map Building [1]. Although for many tasks these systems perform well, a considerable number of issues remain to be solved if compared to biological systems that routinely exhibit adaptive locomotion and navigation tasks in complex environments with great ease and robustness.

The studies of physiology and biomechanics revealed that animals' navigation capabilities generally rely on highly distributed mechanisms: object recognition and large-scale planning in the brain, reflexes and basic motor signals in peripheral nervous circuitry, and adaptive musculoskeletal dynamics in the mechanical level, for example. Although the decentralized nature of navigation mechanisms

M. Lungarella et al. (Eds.): 50 Years of AI, Festschrift, LNAI 4850, pp. 134–143, 2007.

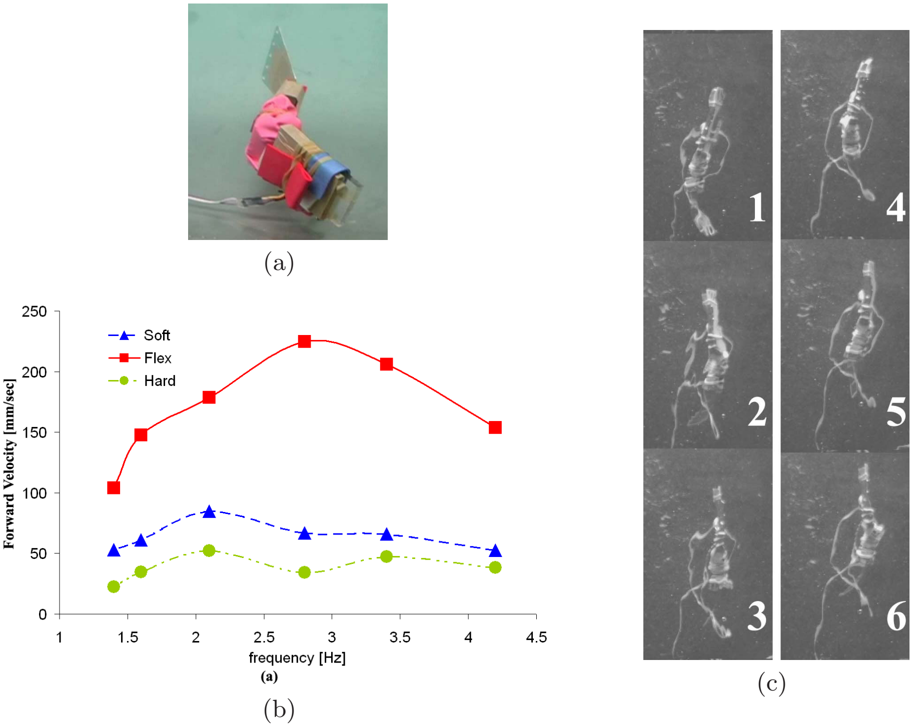
was previously formulated by the so-called Behavior Based Approach [2,3] without explicit internal representation of the world, this approach generally does not explicitly discuss the physics of system-environment interactions, which makes the navigation capabilities still highly limited to relatively simple tasks such as obstacle avoidance and basic target following [4,5].

The computational framework of adaptive control architectures often ignores the fact that every behavior is the result of system-environment interaction, and it is implicitly assumed that computational processes and physical ones are independent problems. There are, however, a number of aspects where the computational processes have to take system-environment interactions into account as discussed in the field of embodied artificial intelligence [6,7,8]. For the navigation problem in particular, there are the following three main reasons. Firstly and most importantly, capabilities and limits of navigation are largely influenced by how robotic systems interact physically with environment. The well-designed mechanical structures are prerequisite for maximum forward speed, maneuverability, and energy efficiency for the locomotion in complex dynamic environment. Secondly, motor control architectures are highly related to the way how the system interacts physically with the environment. With a good mechanical design, computational process of motor control can be significantly simplified as demonstrated by Passive Dynamic Walkers [9,10,11], for example. And thirdly, because the dynamics of physical system-environment interaction are often highly nonlinear, the computational processes such as route planning cannot make decisions arbitrarily, but they need to take the physical constraints into account. For example, as demonstrated later in this article, the physical constraint of underactuated locomotion systems need to exploit the dynamics of hopping behavior in order to traverse rough terrains.

This article introduces three projects of locomotion machines with a special focus on underactuated systems, i.e. the systems that exploit passive dynamics for their behavioral functions. These case studies demonstrate how behavioral performances such as rapid movement, behavioral diversity, and complex behavior patterns can be improved in underactuated robotic systems by taking advantage of the interplay between material properties, body structures and dynamics, and adaptive control processes. Based on these case studies we will speculate further challenges and perspectives of robot navigation.

2 “Cheap Design” for Locomotion

Complex mechanical structures are a fertile basis of animals’ adaptive behavior. Likewise, well-designed structures and mechanical properties of robot body are an important prerequisite, which make the robotic systems capable of achieving many behavioral variations for the purpose of adaptive behavior in complex dynamic environment. Exploiting physical constraints of the systems’ own body and ecological niche is essential not only for energy efficient, rapid behavior with high maneuverability, but also simplified control, as nicely formulated by the principle of “cheap design” [6][8]. This section explains how physical



(a)

(b)

(c)

Fig. 1. Behavioral dynamics of the fish robot. (a) Photograph of the fish robot. (b) Forward velocity of three types of tail fins made of different materials (Square plot: flexible fin, triangle plot: soft fin, and circle plot: hard fin). (c) Time-series photographs of a typical forward swimming of the fish robot.

system-environment interactions can be exploited to achieve locomotion functions through a case study of an underwater locomotion robot. This "cheap" underwarter locomotion nicely demonstrates how locomotion capabilities are dependent on the physical system-environment interaction induced by mechanical design.

The fish robot has one single degree-of-freedom of actuation: it can basically wiggle its tail fin back and forth. The motor connects a rigid frontal plate and the elastic tail fin (Figure 1(a)). With this body structure, simple motor oscillation drives this fish robot not only in the forward direction, but also right, left, up, and down by exploiting fluidic friction and buoyancy [12]. Turning left and right is achieved by setting the zero-point of the wiggle movement either left or right at a certain angle. The buoyancy is such that if it moves forward slowly, it will sink (move down). The forward swimming speed is controlled by wiggling frequency and amplitude. If it moves fast and turns, its body will tilt slightly to one side which produces upthrust so that it will move upwards. For these behavioral variations, therefore, control of forward speed plays an important role. It is generated by the fluid dynamics as the elastic fin interacts with the environment. If the robot has inappropriate material properties in the tail fin, the locomotion performance is significantly degraded. Figure 1(b) shows how the forward velocity is related to the oscillation frequency of the motor and the material properties of tail fin.

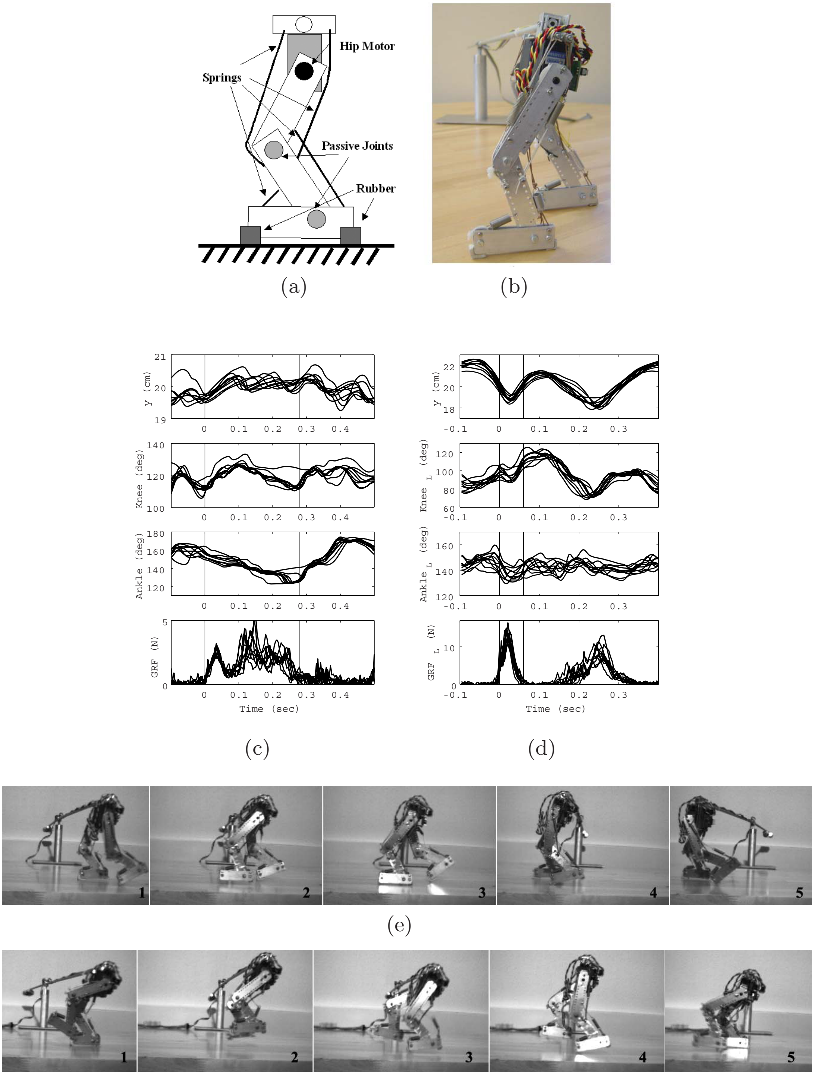
This case study provides a nice illustration of how a computational process of motor control is related to the mechanical structure of the robot. The locomotion function is a consequence of physical system-environment interaction, i.e. the interaction between the frontal plate, the tail fin and the fluid, and the actuation simply induces the particular dynamic interaction. As a result, the control architecture can be very simple (oscillation of one motor). Another notable implication is the fact that the material properties of the robot body become important control parameters when motor control exploits the system-environment interaction. By changing the material property of the tail fin only, the same kinematic movement of the motor can result in fast or slow forward velocity.

3 Body Dynamics for Behavioral Diversity

Physical interaction is important not only in underwater locomotion but also for locomotion on the hard terrain. In this section we introduce a biped robot, which demonstrates two gait patterns - walking and running - by exploiting the dynamics induced by elastic legs interacting with the ground. This case study shows how behavioral diversity can be generated through a particular body structure and its dynamics.

Inspired from biomechanical models of human legs [13,14,15], each leg of this biped robot has one servomotor at the hip and two passive joints at the knee and the ankle (Figure 2(a)). Four springs, which are used to mimic the biological muscle-tendon systems, constrain the passive joints. Three of the springs are connected over two joints: they correspond to the biarticular muscles in the biological systems (i.e. two springs attached between the hip and the shank, another one between the thigh and the heel). Essentially, biarticular muscles induce more complex dynamics because the force exerted on each spring is not only dependent on the angle of a single joint but also the angle of the other joint. Interestingly, however, this unique design of the elastic legs enables the system to induce two different gait patterns, walking and running, by using a basic oscillation of the hip motors.

Despite the simplicity of the motor control, the leg behavior of walking is surprisingly similar to that of human [16]: As shown in Figure 2(c,e), during a stance phase, the body trajectory exhibits multiple peaks in vertical movement, the knee joint exhibits multiple flexion and extension movements, and the ankle joint rotates rapidly at the end. We found that these characteristics of joint trajectories are common also in human walking behavior. With the same configuration of the body design, this robot is also capable of running by varying the spring constants and a few motor oscillation parameters. As shown in



(a) (b)

(c) (d)

(e)

(f)

Fig. 2. Dynamic biped walking and running. (a) Schematic illustration and (b) photograph of the biped robot. This robot consists of a joint controlled by a servomotor (represented by a black circle) and three leg segments which are connected through two passive joints (gray circles). Four tension springs are attached to the segments and rubber materials are implemented at the two ground contact points of the foot body segment. The robot is attached to a pole to restrict rotational movement of the body. (c)Walking and (d) running dynamics are illustrated in terms of the vertical movement of body, knee joint angle, ankle joint angle, and vertical ground reaction force GRF (from top to bottom) which are aligned by the stance phase of 10 steps (the stance phase is indicated by two vertical lines in the figures). Time-series trajectories of the robot (c) walking and (d) running.

Figure 2(d,f), the robot shows a clear flight phase of about 0.1 second, resulting from the complex dynamics of the body and joint trajectories significantly different from those of walking [17].

This case study demonstrated how different kinds of behavioral patterns can be essentially generated by the body dynamics which are necessary in the adaptive locomotion scheme. By carefully designing elastic body structures, behavioral diversity can be not only achieved by the computational processes of motor control, but also significantly influenced by the dynamics induced by the interactions with simple motor action and the ground reaction force.

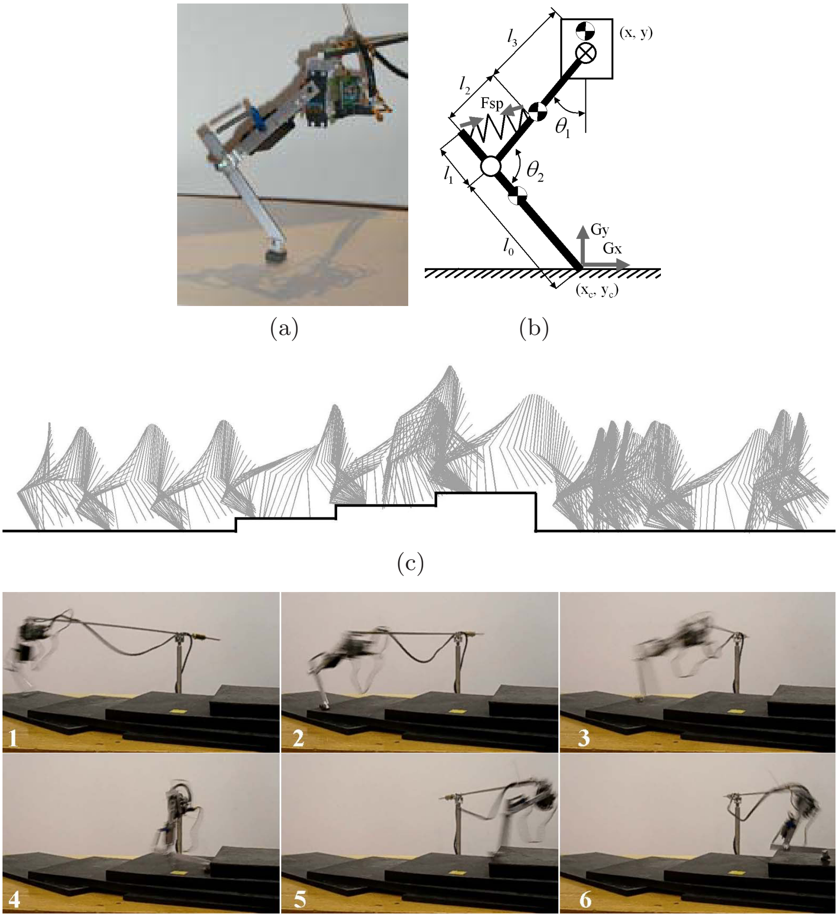
4 Control and Learning Through Body Dynamics

As shown in the previous sections, the use of body dynamics has a great potential to significantly improve the physical locomotion performances by using very simple control. However, a fundamental problem in control of underactuated systems lies in the fact that the desired behavior is always dependent on the environmental conditions. When the conditions are changed, the same motor commands result in a different behavior, and it is difficult to find the new set of motor commands in the new environment. In other words, the behavior is coupled with environmental properties, which the system could actually take advantage of. For example, the velocity curves of the fish robot are dramatically changed in rapid water flow or turbulence, and the biped walking and running is no longer possible in insufficient ground friction or a soft surface. In this sense, a dynamic adaptive controller is an essential prerequisite for underactuated systems.

This section introduces a case study of a hopping one-legged robot that learns motor control in order to traverse rough terrains [18]. This robot consists of one servomotor at the hip joint and two limb segments that are connected through a passive joint and a linear tension spring (Figure 3(a,b)). Although, on a level ground, this underactuated system exhibits periodic stable running locomotion with a simple oscillation of the actuator [19], it requires dynamic control of parameters in order to negotiate with large changes in the environment such as a series of large steps.

In this experiment, we applied a simple machine learning method, the so-called Q-learning algorithm, for optimizing the oscillation frequency of the actuated joint. The system optimizes the motor frequency of every leg step to induce adequate hopping to jump over relatively large steps on the terrain. The sequence of motor frequency is learned through the positive reward proportional to the travelling distance and negative reward in case of fall. Because the learning process requires a number of iterations, we conducted the control optimization in simulation and the learned parameters were transferred to the real-world robotic platform. After a few hundred iterations of the simulation, the system is able to find a sequence of frequency parameters that generates a hopping gait of several leg steps for the locomotion of the given rough terrain (Figure 3(c,d)).

In general, the control architectures of underactuated systems are highly nonlinear in a sense that hopping height and forward velocity of this one-legged



(a) (b)

(c)

(d)

Fig. 3. One-legged hopping robot traversing rough terrains. (a) Photograph and (b) schematic of the one-legged hopping robot, that consists of one servomotor at the hip joint and two limb segments connected through compliant passive joint. (c) Optimization results of motor control in simulation. The optimized sequence of motor frequency exhibits 12 leg steps successfully travelling through a rough terrain. (d) Time-series photographs of the robot hopping over the steps. The motor control parameter was first optimized in simulation and transferred to the robot for the real-world experiment.

robot, for example, are not fully proportional to the motor oscillation frequency. Therefore, in order to achieve locomotion in complex environment, it is necessary to have adaptive control architectures such as a learning process shown in this case study. However, if the mechanics is properly designed, these adaptive control architectures can be kept quite simple. In fact the optimization process of the one-legged robot searches a sequence of one control parameter only, i.e. the frequency of motor oscillation. Simplicity of control results in a reduced parameter space and less exploration, which leads to considerable speed-up of the learning process.

5 Discussion: Challenges and Perspectives

In the navigation studies in general, means of locomotion and body structures are not explicitly considered, and the research is typically centered around the issues of sensing, modelling of the environment, and planning. However, this article showed that it is essential to investigate physical system-environment interactions in locomotion in order to scale up the performance and complexity of navigation tasks significantly. In this section, we elaborate how the dynamics of underactuated systems is related to a new framework of navigation based on the case studies presented.

One of the most fundamental open problems is still in the level of mechanics. Generally the exploitation of mechanical properties in underactuated systems provides energy efficiency [11,20], recovery of periodic behavioral patterns from disturbances [9,21,22,25], and the increase of behavioral variations derived from body dynamics [26,23,24]. While we still do not fully understand how to design "adaptive mechanics", it is important to note that mechanics is significantly related to motor control and perception, hence navigation and locomotion cannot be independent problems.

Another challenge lies in the adaptive dynamic control architecture, which is a prerequisite for underactuated systems as explained in the case study of the one-legged hopping robot. It is still an active research topic, and a number of different approaches are currently investigated (e.g. [27,28,29,30]). Along this line of research, we expect to understand how underactuated systems will actively explore their body dynamics. By obtaining the capabilities and limits of their own body, they will be able to deal rapidly and precisely with complex environment.

Although we have not explicitly discussed so far how perception processes are related to mechanical properties and motor control, it is a highly important issue in the context of navigation. In fact, the use of body dynamics can be used for better sensing [31]. Because the sensing and the recognition processes are fundamental open problems in navigation, underactuated systems should be investigated further in order to gain a comprehensive understanding of the sensory-motor processes.

Acknowledgement

This work is supported by the Swiss National Science Foundation (Grant No. 200021-109210/1), the Swiss National Science Foundation Fellowship for Prospective Researchers (Grant No. PBZH2-114461), and the German Research Foundation (DFG, SE1042). The authors would like to appreciate Marc Ziegler, Jürgen

Rummel, Gabriel Gomez, Alex Schmitz, and Russ Tedrake for the fruitful discussion and collaboration during the robotic experiments presented in this article.

References

1. Leonard, J.J., Durrant-Whyte, H.F.: Simultaneous map building and localization for an autonomous mobile robot. In: IEEE/RSJ International Workshop on Intelligent Robots and Systems, pp. 1442–1447 (1991)
2. Brooks, R.A.: Intelligence without representation. Artificial Intelligence 47, 139–159 (1991)
3. Arkin, R.C.: Behavior-based robotics. MIT Press, Cambridge (1998)
4. Brooks, R.A.: A robot that walks: Emergent behaviors from a carefully evolved network. Neural Computation 1(2), 253–262 (1989)
5. Braitenberg, V.: Vehicles - Experiments in synthetic psychology. MIT Press, Cambridge (1984)
6. Pfeifer, R., Scheier, C.: Understanding Intelligence. The MIT Press, Cambridge (1999)
7. Iida, F., Pfeifer, R., Steels, L., Kuniyoshi, Y. (eds.): Embodied Artificial Intelligence. LNCS (LNAI), vol. 3139. Springer, Heidelberg (2004)
8. Pfeifer, R., Iida, F., Bongard, J.: New robotics: Design principles for intelligent systems. Artificial Life 11(1-2), 99–120 (2005)
9. McGeer, T.: Passive Dynamic Walking. The International Journal of Robotics Research 9(2), 62–82 (1990)
10. Collins, S.H., Wisse, M., Ruina, A.: A three-dimentional passive-dynamic walking robot with two legs and knees. International Journal of Robotics Research 20, 607–615 (2001)
11. Collins, S., Ruina, A., Tedrake, R., Wisse, M.: Efficient bipedal robots based on passive dynamic walkers. Science Magazine 307, 1082–1085 (2005)
12. Ziegler, M., Iida, F., Pfeifer, R.: “Cheap” underwater locomotion: Roles of morphological properties and behavioural diversity. In: Proceedings of Climbing and Walking Robots (2006)
13. McMahon, T.A., Cheng, G.C.: The mechanics of running: How does stiffness couple with speed? Journal of Biomechanics 23(suppl. 1), 65–78 (1990)
14. Blickhan, R.: The spring-mass model for running and hopping. Journal of Biomechanics 22, 1217–1227 (1989)
15. Seyfarth, A., Geyer, H., Guenther, M., Blickhan, R.: A movement criterion for running. Journal of Biomechanics 35, 649–655 (2002)
16. Iida, F., Minekawa, Y., Rummel, J., Seyfarth, A.: Toward a human-like biped robot with compliant legs. In: Arai, T., et al. (eds.) Intelligent Autonomous Systems - 9, pp. 820–827. IOS Press, Amsterdam (2006)
17. Iida, F., Rummel, J., Seyfarth, A.: Bipedal walking and running with compliant legs. In: International Conference on Robotics and Automation (ICRA 2007), pp. 3970–3975 (2007)
18. Iida, F., Tedrake, R.: Motor control optimization of compliant one-legged locomotion in rough terrain. In: Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2007) (in press, 2007)
19. Rummel, J., Iida, F., Seyfarth, A.: One-legged locomotion with a compliant passive joint. In: Arai, T., et al. (eds.) Intelligent Autonomous Systems – 9, pp. 566–573. IOS Press, Amsterdam (2006)

20. Buehler, M., Battaglia, R., Cocosco, A., Hawker, G., Sarkis, J., Yamazaki, K.: Scout: A simple quadruped that walks, climbs and runs. In: Proc. Int. Conf on Robotics and Automation, pp. 1707–1712 (1998)
21. Kubow, T.M., Full, R.J.: The role of the mechanical system in control: a hypothesis of self-stabilization in hexapedal runners. Phil. Trans. R. Soc. Lond. B 354, 849–861 (1999)
22. Raibert, H.M.: Legged Robots That Balance. MIT Press, Cambridge (1986)
23. Iida, F., Pfeifer, R.: "Cheap" rapid locomotion of a quadruped robot: Self-stabilization of bounding gait. In: Groen, F., et al. (eds.) Intelligent Autonomous Systems 8, vol. 35, IOS Press, Amsterdam (2004)
24. Iida, F., Gomez, G.J., Pfeifer, R.: Exploiting body dynamics for controlling a running quadruped robot. In: ICAR 2005, July 18th-20th, Seattle, U.S.A. pp. 229–235 (2005)
25. Cham, J.G., Bailey, S.A., Clark, J.E., Full, R.J., Cutkosky, M.R.: Fast and robust: hexapedal robots via shape deposition manufacturing. The International Journal of Robotics Research 21(10), 869–882 (2002)
26. Raibert, M.H.: Trotting, pacing and bounding by a quadruped robot. Journal of Biomechanics 23(suppl. 1), 79–98 (1990)
27. Taga, G., Yamaguchi, Y., Shimizu, H.: Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment. Biological Cybernetics 65, 147–159 (1991)
28. Tedrake, R., Zhang, T.W., Seung, H.S.: Stochastic policy gradient reinforcement learning on a simple 3D biped. In: Proc. of the 10th Int. Conf. on Intelligent Robots and Systems, pp. 2849–2854 (2004)
29. Geng, T., Porr, B., Wörgötter, F.: A reflexive neural network for dynamic biped walking control. Neural Computation 18(5), 1156–1196 (2006)
30. Buchli, J., Iida, F., Ijspeert, A.J.: Finding resonance: Adaptive frequency oscillators for dynamic legged locomotion. In: Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2006), pp. 3903–3909 (2006)
31. Iida, F., Pfeifer, R.: Sensing through body dynamics. Robotics and Autonomous Systems 54(8), 631–640 (2006)