Biologically Inspired Motor Control for Underactuated Robots: Trends and Challenges

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Abstract There has been an increasing interest in the study of underactuated robotics toward significant improvement of behavioral performances in robotic systems. The previous studies on underactuated robots have demonstrated energy efficient, maneuverable, and robust motion control by properly exploiting passive dynamics. Despite these fascinating characteristics in underactuated systems, however, there are a few particularly important challenges which are related to the control of nonlinear dynamics derived from physical interactions with the environment. Because passive dynamics induces nonlinear system-environment interactions, it is highly difficult to develop control architectures for the precise control of the systems, and thus they are able to exhibit only limited variations of behavior patterns. In order to tackle with the challenges, this article will discuss three important research directions that we have been pursuing, i.e. mechanical feedback for self-stability, design optimization for behavioral diversity, and control optimization for precise motor control and planning.

1 Introduction

If compared with biological systems that routinely exhibit dynamic behaviors in complex environment with surprising adaptivity, energy efficiency and robustness, our robots are still severely suffering from the lack of sensory-motor and learning capabilities [1]. To account for the discrepancy of behavior control in animals and robots, there has been an increasing interest in the study of underactuated robotic systems for rapid, efficient and maneuverable behaviors in the real world.

Underactuated robots designate the robotic systems that have joints in their body that are not actuated, thus their behaviors are constrained by passive dynamics. In

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contrast to fully actuated systems, this approach characterizes the motion control in biological systems leading to the following three major advantages. First, because underactuated systems have less number of motors, and a large part of behavior is regulated by passive dynamics, they have a better possibility to increase energy efficiency. Passive Dynamic Walkers (PDWs, [2, 3, 4]), for example, are capable of walking down the shallow slope without any actuation or control by exploiting passive dynamics of the mechanical structures. Second, although speed of movement in fully actuated systems is generally limited by the maximum speed of the actuators, underactuated systems have a better possibility to increase speed of their motion by exploiting passive dynamics. Third, underactuated systems have significantly less numbers of motors and sensors, they generally have simpler mechanical structures and control architectures. This results in not only simpler mechanical implementation of motors and sensors but also less demands in control architectures. It is often the case that, for example, control frequency of underactuated systems can be significantly lower than the requirements often used in fully actuated systems. And fourth, as it becomes clear later in this article, underactuated systems are able to exploit mechanical self-stability to regulate their behavior patterns.

While underactuated systems can benefit from these advantages, there are a number of challenges in this approach. One of the most significant challenges lies in the fact that, in order to precisely control motions of underactuated systems, they have to deal with highly nonlinear mechanical dynamics. This can be regarded as a control problem of a double or triple pendulum, for example. Second, the design process of underactuated systems are generally highly complex. The complexity in design processes, is generally originated in the fact that the designers have to consider many mechanical design parameters (such as mass distributions, friction in passive joints, moment of inertia, etc.) to exploit passive dynamics for behavior control. And third, another significant challenge is behavioral diversity. Because of the nonlinear dynamics and complex design processes, most of the underactuated systems so far are able to exhibit only one or two behavior patterns, and limited adaptability against environmental variations.

Although these challenges are not trivial, there are a few potentially interesting research directions which, we believe, significantly contribute to the progress in this exciting research domain. In this article, we discuss three technological challenges that will potentially lead to a significant breakthrough to deal with underactuated systems that can be controllable while appreciating eminent benefits derived from passive dynamics. Note that this article shows only the important aspects of the case studies in order to discuss conceptual issues. More technical details can be found in the corresponding publications [5, 6, 7, 8].

2 Mechanical Feedback for Self-Stability

One of the most fascinating aspects of underactuated systems lies in the fact that, if designed properly, motions can be mechanically regulated. As nicely demonstrated

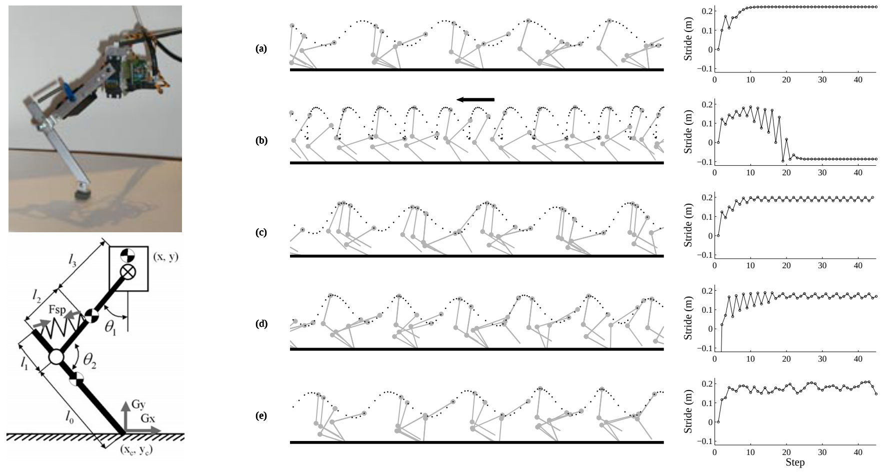


Fig. 1 Self-stability and variations of locomotion processes in a one-legged hopping robot: (a) stable forward locomotion with a constant stride length, (b) backward locomotion, (c, d) forward locomotion with two and three step cycles, (e) stable locomotion with chaotic stride lengths. The oscillation frequencies of the hip motor are $f = 2.78, 2.72, 2.85, 2.78, 2.73$ Hz (from top to bottom) [5, 8].

in the case studies of PDWs, some behavior patterns can be induced without sensing, trajectory computation, or actuation, and undesired deviation of motion patterns derived from the system-environment interactions can be mechanically adjusted.

For a systematic exploration of mechanical feedback for self-stability, here we discuss one of the simplest legged robot models shown in Figure 1. This robot consists of one motor at the hip joint and two limb segments connected through an elastic passive joint. This system requires only a simple motor oscillation to stabilize itself into a periodic hopping behavior [9, 10]. The hip motor uses a position feedback control, in which the angle of hip joint is determined by a synchronized sinusoidal oscillation with three parameters: amplitude, frequency, and offset of oscillation.

When these parameters are set properly, the robot shows stable periodic hopping behaviors (Figure 1), and behavioral characteristics resulting from its particular morphology can be summarized as follows. First, locomotion can only be achieved dynamically. Since the leg has one single actuated degree of freedom, the only way the robot can lift its legs off the ground is by delivering enough energy through the motors to make the whole body jump. Second, stability is achieved through the material properties of the legs (especially the compliance of the passive joints) rather than by actively controlling the positions of all joints. For instance, an inadequate position of the lower limb (which is only passively attached to the upper limb) during the flight phase will automatically be corrected by the spring on contact with the ground. In particular, this characteristic allows the robot to be controlled in an open-loop manner (i.e. without any sensory feedback) over a continuous range of control parameters. By simply actuating periodically the motors back and forth, the robot put on the ground will automatically settle after a few steps into a natural and stable running rhythm. Third, the elasticity of the legs, partially storing and releasing energy during contact with the ground, allows to achieve not only stable, but also rapid and energy efficient locomotion. The importance of such elastic properties in muscle-tendon systems has been long recognized in biomechanics, where it has a particular significance in theoretical models for the locomotion of legged animals [11, 12, 13].

Mechanical feedback for self-stable periodic behaviors is not a unique property of this particular model only, but there have been a number of different models reported in the past. For example, in the biological studies, the concept of mechanical feedback explains many aspects of animals' legged locomotion [13, 14, 15, 16, 17], and based on the concept, a number of robotics platforms have successfully demonstrated rapid and robust locomotion [18, 19, 20, 6, 21]. Based on these minimalistic models of mechanical self-stability, one of the major challenges is to systematically explore the basic mechanisms of self-stability including additional functional elements such as adjustable spring-damper regulators and basic feedback loops (e.g. reflexes).

3 Body Dynamics for Behavioral Diversity

While the theoretical investigations of mechanical feedback are highly interesting on its own right and still require additional insights, an exciting research direction is to consider the nonlinear body dynamics derived from morphological constraints while keeping the modest control efforts. In this section, we discuss the roles of morphology in underactuated systems with respect to behavioral diversity: most of underactuated robots are able to achieve only a few periodic behavioral patterns, and they still suffer from variability of behaviors. In fact, the PDWs can walk in a specific environment and they can not easily vary locomotion speed or stride length, for example. In order to tackle with the problem of behavioral diversity, this section introduces a case study of exploring the roles of morphological properties, in which behavioral diversity can be increased while maintaining fascinating characteristics of underactuated systems.

Inspired from biomechanical models of human legs [11, 16, 17], we developed a biped robot which demonstrates two gait patterns - walking and running - by exploiting the nonlinear dynamics induced by elastic legs interacting with the ground. 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 bi-

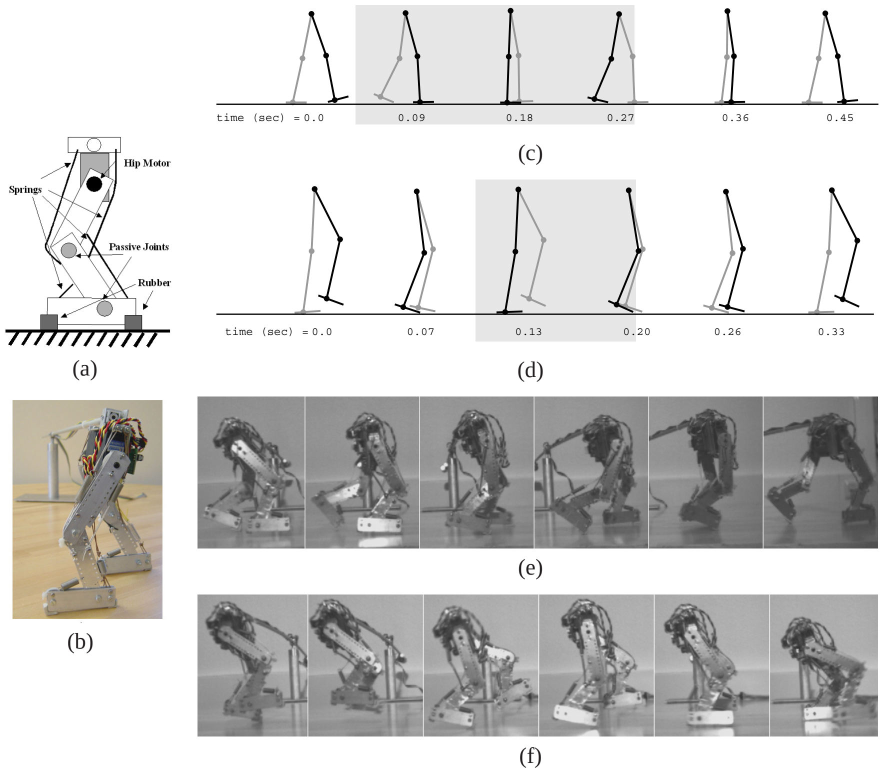


Fig. 2 Biped robot with passive knee and ankle joints which are constrained by biarticular springs (a,b). One cycle behavior of the model in simulation: (c) walking and (d) running. Black and gray leg segments represent the right and left leg, respectively, and gray areas depict the stance phase of the right leg. The cycle time is set to 0.45 sec ($\omega = 2.2$Hz) for walking, and 0.33 sec ($\omega = 3.0$Hz) for running. The flight phase of running is approximately 0.06 sec before and after the stance phase. Time-series photographs of the biped robotic platform during (e) walking and (f) running. A high-speed camera was used to record the experiments (Basler A602fc: resolution 656x490 pixels, frame rate 100fps). The interval between two pictures is approximately 10ms [6].

ological 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 [6]: As shown in Figure 2, the body trajectory exhibits both single and double support phases, and the knee joint stretched to straight during the single support phase, which are common also in human walking behavior. With

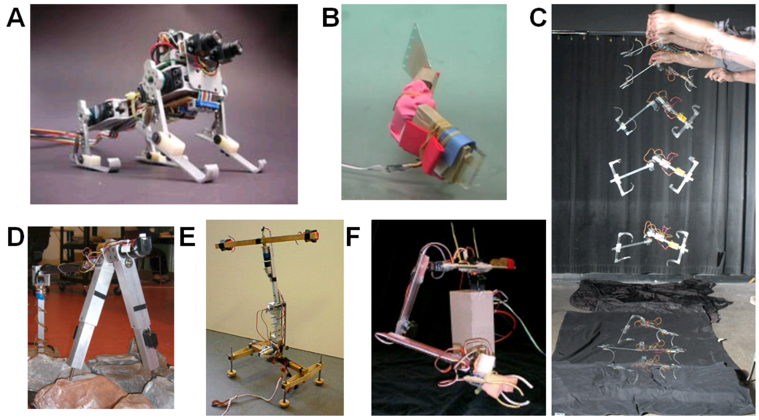


Fig. 3 The photographs of representative robots that we developed for the exploration of morphology, dynamics, behavior control. B: Running dog robot MiniDog [20], C: Cheap swimming robot Wanda [22], D: Falling cat robot, E: Compass gait biped robot [8], F: Dancing robot Stumpy [23], G: Dynamic arm robot Cook.

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 also shown in Figure 2, 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 [6]. 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.

As exemplified in this case study, morphological designs play important roles in underactuated systems. Figure 3 shows some of our explorations on the different roles of morphological properties in underactuated systems. Very briefly, we have identified that compliant leg behaviors are useful for controlling dynamic locomotion of four-legged robot [20]; elastic material properties could generate efficient underwater locomotion [22]; mass distribution helps controlling body posture of falling cat robot and upper body dynamics for versatile dynamic locomotion [23]. It is important to note that, owing to the well-designed body structures in these robots, they are able to achieve the dynamic behavior control in a very simple manner.

So far we explored a number of different morphological parameters that play roles of motion control in underactuated systems, but an interesting challenge is to identify how to induce substantially different behavioral patterns by manipulating these morphological parameters on the fly. Unlike active feedback based on joint torque regulations, manipulation of morphological parameters is expected to provide a new motion control scheme with energy efficient self-stability at a low control frequency.

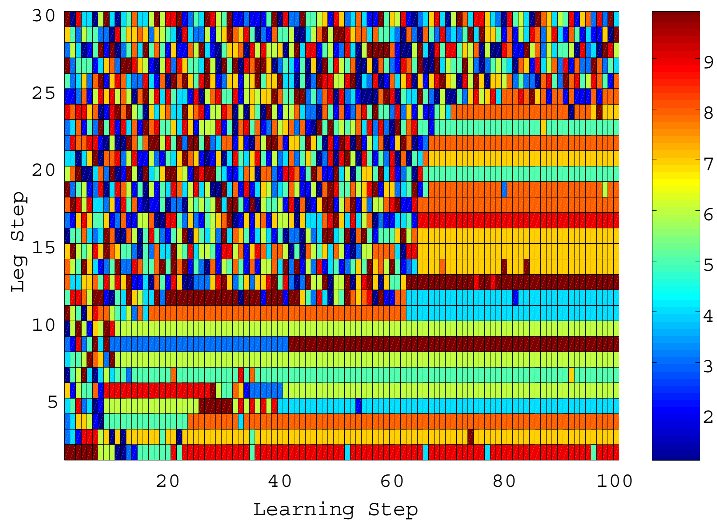
4 Controlling Nonlinear Dynamics

While the design considerations for mechanical feedback are of significant importance in the underactuated robotics research, control of kinematic trajectories is still a significant challenge because of nonlinear dynamics derived from passive dynamics. In general, the control problem of underactuated systems can be characterized by the facts that (a) kinematic trajectories of underactuated systems are only partially controllable, and (b) control actions have long-term consequences. In the previous case study of one-legged hopping robot, for example, controlling foot placement is a highly difficult issue because body trajectories are constrained by behaviors of the passive compliant leg, and the change of control parameters in the hip motor would not only influence the immediate body movement but also the movement over a few steps.

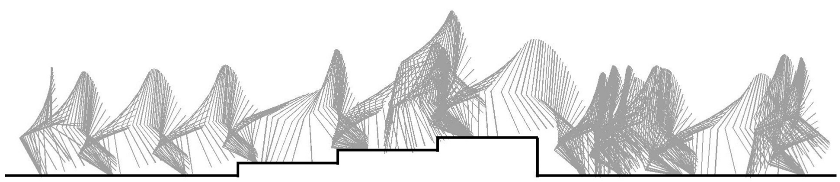
In this section, we explore the possibility of using computational optimization tools to tackle with this problem. The use of computational tools is particularly interesting because the reasoning of nonlinear dynamics can be automatically handled by evaluation of single scalar value (reward signals), although it requires relatively long-term optimization processes. More specifically, we make use of a simple machine learning method, the so-called Q-learning algorithm [24], applied for the hopping robot traveling over a rough terrain.

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 traveling distance and negative reward in case that the robot falls over. 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 4).

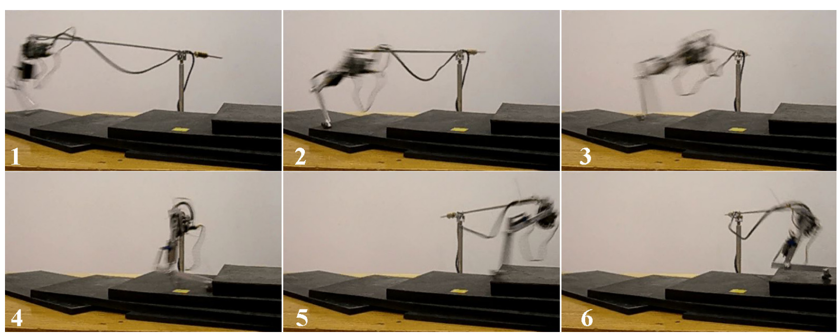
There are a few important implications in this case study. First, even though we used only single scalar value for the evaluation of locomotion process, the optimization process is able to reason about the consequences of motor actions in the sequence of locomotion steps, which is due to the reward propagation mechanism in the reinforcement learning algorithm. In Figure 4(a), for example, the learning process could not find the adequate parameter at the leg step 12 (after the learning step 17), it had to explore the parameter space until the parameter change at the leg step 9 (at the learning step 42), which eventually resulted in a breakthrough to continue the locomotion thereafter. And second, the learning process in this experiment can be kept quite simple because the mechanical self-stability was exploited. In fact the optimization process of the one-legged robot searches a sequence of one control



(a)



(b)



(c)

Fig. 4 (a) A learning process of motor control policies. The color in each tile indicates the oscillation frequency of motor at the leg step N. It is shown that the control policy is structured toward the end of the learning process. One-legged hopping robot traversing rough terrains. (b) Optimization results of motor control in simulation. The optimized sequence of motor frequency exhibits 12 leg steps successfully traveling through a rough terrain. (c) 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 [5, 8].

parameter only, i.e. the frequency of motor oscillation. Simplicity of the controller results in a reduced parameter space and less exploration, which leads to considerable speed-up of the learning process.

While this case study is a significant first step which implies important requirements for motor control learning in underactuated systems, there are still a number of challenging issues to be solved. One of the most significant challenges seems to be how to reduce the number of trial-and-error iterations. Although the learning architecture exploiting self-stability already reduced learning steps, the system introduced above has to repeat the entire learning process whenever it encounters a new environment. To cope with this problem, it is necessary to investigate how we could design more generalized state representations, and furthermore, how the system could generate autonomously an appropriate mechanical model of its own body [25]. In addition, while we used an explicit reward signals (i.e. the distance traveled) in the case study above, a learning architecture driven by implicit reward signals is another exciting research topic which is a prerequisite for autonomous adaptive systems [7, 8].

5 Conclusion

While underactuated systems have a set of beneficial properties such as energy efficiency, maneuverability, and mechanical self-stability, there are still a few fundamental problems, which are related to complex design processes of nonlinear mechanical dynamics, and precise and robust control of them. For a significant breakthrough toward useful robotic applications, this paper introduced a few recent achievements in our underactuated robotics research. For a systematic exploration of this challenging research domain, it is particularly important to obtain a comprehensive understanding of mechanical feedback for self-stability, which is a promising basis to improve design optimization of complex underactuated systems as well as nonlinear control optimization, as briefly explained in this paper. It is also important to note that the challenges discussed in this papers are common not only in legged locomotion robots, but also in surprisingly many hard problems of robotics such as flying and swimming robots, grasping of unknown objects, and physical contacts in man-machine systems, for example. By investigating these challenges, therefore, we expect to provide a broad impact in robotics.

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