Efficient Bipedal Robots Based on Passive-Dynamic Walkers

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Passive-dynamic walkers are simple mechanical devices, composed of solid parts connected by joints, that walk stably down a slope. They have no motors or controllers, yet can have remarkably humanlike motions. This suggests that these machines are useful models of human locomotion; however, they cannot walk on level ground. Here we present three robots based on passive-dynamics, with small active power sources substituted for gravity, which can walk on level ground. These robots use less control and less energy than other powered robots, yet walk more naturally, further suggesting the importance of passive-dynamics in human locomotion.

Most researchers study human locomotion by observing people as they walk, measuring joint angles and ground reaction forces (*1*). Our approach is different: We study human locomotion by designing and testing walking machines that we compare to humans in terms of morphology, gait appearance, energy use, and control.

Previous bipedal robots with humanlike forms have demonstrated smooth, versatile motions (*2–5*). These impressive robots are based on the mainstream control paradigm, namely, precise joint-angle control. For the study of human walking, this control paradigm is unsatisfactory, because it requires actuators with higher precision and frequency response than human muscles have (*6*) and requires an order of magnitude more energy. To address these issues, passive-dynamic walkers (Fig. 1) were proposed as a new design and control paradigm (*7*). In contrast to mainstream robots, which actively control every joint angle at all times, passive-dynamic walkers do not control any joint angle at any time. Although these walkers have no actuation or control, they can walk downhill with startlingly humanlike gaits (*8*).

To demonstrate that the humanlike properties of passive-dynamic machines are not dependent on gravitational power, but rather extend to level-ground walking, we built three powered walking robots (Fig. 2) at three institutions, substituting gravitational power with simple actuation. The Cornell biped (Fig. 2A) is based on the passive device in Fig. 1D and is powered by electric motors with springs that drive ankle push-off. It has five internal degrees of freedom (two ankles, two knees, and a hip), each arm is mechanically linked to the opposite leg, and the small body is kinematically constrained so that its midline bisects the hip angle. The Delft biped (Fig. 2B) has a similar morphology, but it is powered by pneumatic hip actuation and has a passive ankle. The Massachusetts Institute of Technology (MIT) learning biped (Fig. 2C) is based on the simpler ramp-walkers in Fig. 1, A and B. It has six internal degrees of freedom (two servo motors in each ankle and two passive hips), each arm is mechanically linked to the opposite leg, the body hangs passively, and it uses reinforcement learning to automatically acquire a control policy. The supporting online movies show these robots walking and the supporting online text describes their construction details (*9*).

The Cornell biped is specifically designed for minimal energy use. The primary energy losses for humans and robots walking at a constant speed are due to dissipation when a foot hits the ground and to active braking by the actuators (negative work). The Cornell design demonstrates that it is possible to completely avoid this negative actuator work. The only work done by the actuators is positive: The left ankle actively extends when triggered by the right foot hitting the ground, and vice versa. The hip joint is not powered, and the knee joints only have latches. The average mechanical power (*10*) of the two ankle joints is about 3 W, almost identical to the scaled gravitational power consumed by the passive-dynamic machine on which it is based (*8*). Including electronics, microcontroller, and actuators, the Cornell biped consumes 11 W (*11*).

To compare efficiency between humans and robots of different sizes, it is convenient to use the dimensionless specific cost of transport, c_t = (energy used)/(weight × distance traveled). In order to isolate the effectiveness of the mechanical design and controller from the actuator efficiency, we distinguish between the specific energetic cost of transport, c_{et}, and the specific mechanical cost of transport, c_{mt}. Whereas c_{et} uses the total energy consumed by the system (11 W for the Cornell biped), c_{mt} only considers the positive mechanical work of the actuators (3 W for the Cornell biped). The 13-kg Cornell biped walking at 0.4 m/s has $c_{et} \approx 0.2$ and $c_{mt} \approx 0.055$. Humans are similarly energy effective, walking with $c_{et} \approx 0.2$, as estimated by the volume of oxygen they consume (V_{O_2}), and $c_{mt} \approx 0.05$ (*12–14*). Measurement of actuator work on the Delft biped yields $c_{mt} \approx 0.08$. Based on the small slopes that it descends when passive, we estimate the MIT biped to have $c_{mt} \geq 0.02$. Although the MIT and Delft bipeds were not specifically designed for low-energy use, both inherit energetic features from the passive-dynamic walkers on which they are based. By contrast, we estimate the state-of-the-art Honda humanoid Asimo to have $c_{et} \approx 3.2$ and $c_{mt} \approx 1.6$ (*15*). Thus Asimo, perhaps representative of joint-angle controlled robots, uses at least 10 times the energy (scaled) of a typical human.

Control algorithms for state-of-the-art, level-ground walking robots are typically complex, requiring substantial real-time computation. In contrast, the Delft and Cornell bipeds walk with primitive control algorithms. Their only sensors detect ground contact, and their only motor commands are on/off signals issued once per step. In addition to powering the motion, hip actuation in the Delft biped also improves fore-aft robustness against large disturbances by swiftly placing the swing leg in front of the robot before it has a chance to fall forward (*16*, *17*).

The MIT biped (Fig. 2C) is designed to test the utility of motor learning on a passive-dynamic mechanical design. The goal of the learning is to find a control policy that

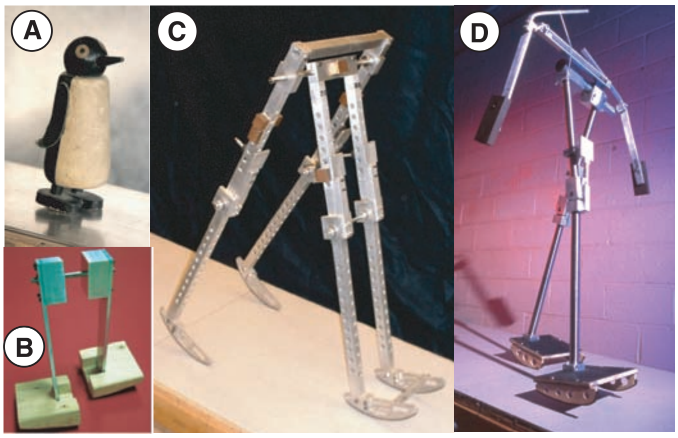

Fig. 1. "Ramp-walking," "downhill," "unpowered," or "passive-dynamic" machines. Our powered bipeds are based on these passive designs. (**A**) The Wilson "Walkie" (*27*). (**B**) MIT's improved version (*28*). Both (A) and (B) walk down a slight ramp with the "comical, awkward, waddling gait of the penguin" (*27*). (**C**) Cornell copy (*29*) of McGeer's capstone design (*7*). This four-legged "biped" has two pairs of legs, an inner and outer pair, to prevent falling sideways. (**D**) The Cornell passive biped with arms [photo: H. Morgan]. This walker has knees and arms and is perhaps the most humanlike passive-dynamic walker to date (*8*).

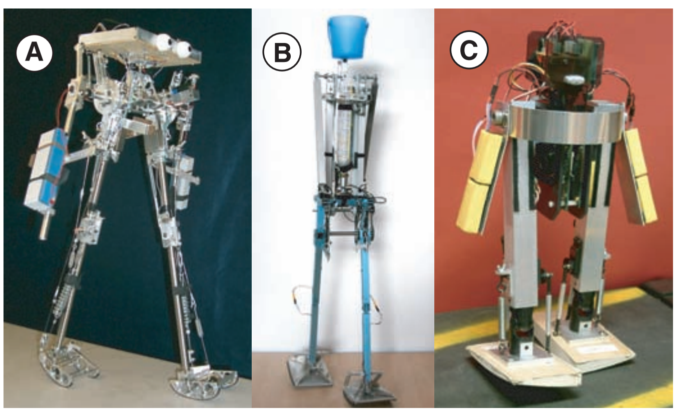

Fig. 2. Three level-ground powered walking robots based on the ramp-walking designs of Fig. 1. (**A**) The Cornell biped. (**B**) The Delft biped. (**C**) The MIT learning biped. These powered robots have motions close to those of their ramp-walking counterparts as seen in the supporting online movies (movies S1 to S3). Information on their construction is in the supporting online text (*9*).

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stabilizes the robot's trajectory on level terrain using the passive ramp-walking trajectory as the target. The robot acquires a feedback control policy that maps sensors to actions using a function approximator with 35 parameters. With every step that the robot takes, it makes small, random changes to the parameters and measures the change in walking performance. This measurement yields a noisy sample of the relation between the parameters and the performance, called the performance gradient, on each step. By means of an actor-critic reinforcement learning algorithm (*18*), measurements from previous steps are combined with the measurement from the current step to efficiently estimate the performance gradient on the real robot despite sensor noise, imperfect actuators, and uncertainty in the environment. The algorithm uses this estimate in a real-time gradient descent optimization to improve the stability of the step-to-step dynamics (Fig. 3). The robot's actuators are mounted so that when they are commanded to their zero position, the robot imitates its passive counterpart. Starting from this zero policy, the learning system quickly and reliably acquires an effective control policy for walking, using only data taken from the actual robot (no simulations), typically converging in 10 min or ~600 steps. Figure 3 illustrates that the learned control policy not only achieves the desired trajectory but is also robust to disturbances. The robot can start, stop, steer, and walk forward and backward at a small range of speeds. This learning system works quickly enough that the robot is able to continually adapt to the terrain (e.g., bricks, wooden tiles, and carpet) as it walks.

Each of the robots here has some design features that are intended to mimic humans. The Cornell and Delft bipeds use anthropomorphic geometry and mass distributions in their legs and demonstrate ankle push-off and powered leg swinging, both present in human walking (*14*, *19*). They do not use high-power or high-frequency actuation, which are also unavailable to humans. These robots walk with humanlike efficiency and humanlike motions (Fig. 4 and movies S1 to S3). The motor learning system on the MIT biped uses a learning rule that is biologically plausible at the neural level (*20*). The learning problem is formulated as a stochastic optimal feedback control problem; there is emerging evidence that this formulation can also describe biological motor learning (*21*).

The Cornell and Delft bipeds demonstrate that walking can be accomplished with extremely simple control. These robots do not rely on sophisticated real-time calculations or on substantial sensory feedback such as from continuous sensing of torques, angles, or attitudes. This implies that steady-state human walking might require only simple control as well; the sequencing of human joint-angles in time might be determined as much by morphology as by motor control. We note that no other robots have done particularly better at generating humanlike gaits even when using high-performance motors, a plethora of sensors, and sophisticated control.

In theory, pushing off just before heel-strike requires about one-fourth the energy of pushing off just after heel-strike (*22*, *23*), so the Cornell robot was initially designed with this preemptive push-off strategy. Initial push-off resulted in both higher torque demands on the motor and a high sensitivity to push-off timing that our primitive control system could not reliably stabilize. Humans seem to solve both of these problems without a severe energy penalty by using a double support phase that overlaps push-off and heel-strike. These issues must also be addressed in the design of advanced foot prostheses.

The success of the Delft robot at balancing using ankles that kinematically couple

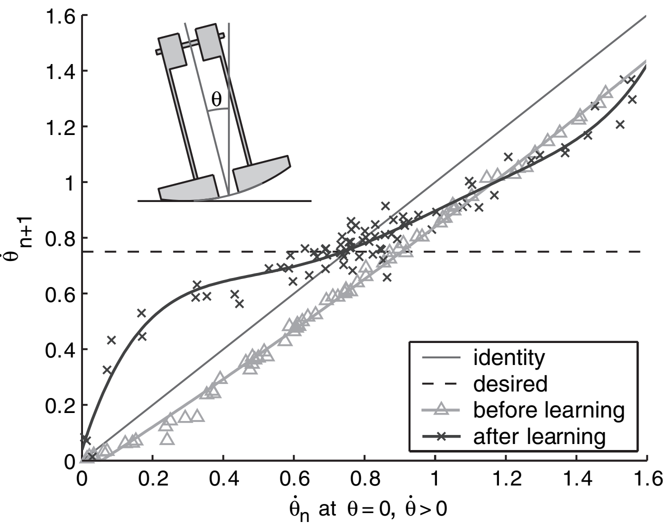

Fig. 3. Step-to-step dynamics of the MIT biped walking in place on a level surface, before (△) and after (x) learning. Shown is the roll angular velocity when the right foot collides with the ground ($\theta = 0$, $\dot{\theta} > 0$) at step $n + 1$ versus step n. Intersections of the plots with the solid identity line are fixed points. The horizontal dashed line is the theoretical ideal; the robot would reach $\dot{\theta} = 0.75\ s^{-1}$ in one step. This ideal cannot be achieved due to limitations in the controllability of the actuation system. On a level surface, before learning, the robot loses energy on every step ($\dot{\theta}_{n+1} < \theta_n$), eventually coming to rest at $\dot{\theta} = 0$. After learning, the robot quickly converges near $\dot{\theta} = 0.75\ s^{-1}$ for $0 \le \dot{\theta}_0 \le 1.7\ s^{-1}$.

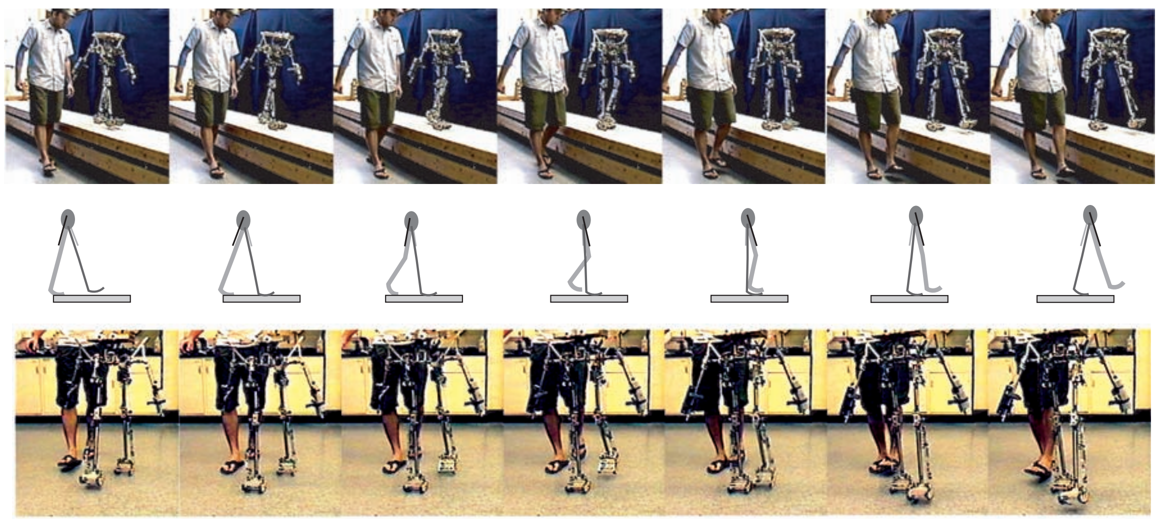

Fig. 4. Two sets of video stills of the Cornell ankle-powered biped walking on a level surface next to a person. A little less than one step is shown at 7.5 frames/s. Both the robot and the person are walking at about 1 step/s. The stick figure indicates the leg angles for the corresponding video stills; the right arm and leg are darker than the left.

leaning to steering hints that humans could similarly use a simple coupling between lean and lateral foot placement to aid balance. Furthermore, simulations used in the development of the Delft robot showed that the swift swing-leg motion not only increased fore-aft stability but also increased lateral stability. Indeed, the physical robot was not able to balance laterally without sufficient fore-aft swing-leg actuation. This highlights the possible coupling between lateral and sagittal balance in human walking.

The MIT biped shows that the efficiency of motor learning can be strongly influenced by the mechanical design of the walking system, both in robots and possibly in humans. Previous attempts at learning control for bipedal robots have required a prohibitively large number of learning trials in simulation (*24*) or a control policy with predefined motion primitives on the robot (*25*). By exploiting the natural stability of walking trajectories on the passive-dynamic walker, our robot was able to learn in just a few minutes without requiring any initial control knowledge. We also found that it was possible to estimate the walking performance gradient by making surprisingly small changes to the control parameters, allowing the robot to continue walking naturally as it learns. This result supports the use of actor-critic reinforcement learning algorithms as models for biological motor learning.

The conclusion that natural dynamics may largely govern locomotion patterns was already suggested by passive-dynamic machines. A common misconception has been that gravity power is essential to passive-dynamic walking, making it irrelevant to understanding human walking. The machines presented here demonstrate that there is nothing special about gravity as a power source; we achieve successful walking using small amounts of power added by ankle or hip actuation.

We expect that humanoid robots will be improved by further developing control of passive-dynamics–based robots and by paying closer attention to energy efficiency and natural dynamics in joint-controlled robots (*26*). Whatever the future of humanoid robots, the success of human mimicry demonstrated here suggests the importance of passive-dynamic concepts in understanding human walking.

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30. The Cornell robot was developed by S.C. with suggestions from A.R.; the Delft robot was developed by M.W. and J. van Frankenhuyzen on an Stichting Technische Wetenschappen grant, with help from A. Schwab; and the MIT robot was developed by R.T. and T. Weirui Zhang with help from M.-f. Fong and D. Tan in the lab of H. Sebastian Seung. A.R. and S.C. were funded by an NSF Biomechanics grant. R.T. was funded by the Packard Foundation and the NSF. The text was improved by comments from N. Agnihotri, C. Atkeson, J. Burns, A. Chatterjee, M. Coleman, J. Grizzle, P. Holmes, I. ten Kate, A. Kun, A. Kuo, Y. Loewenstein, S. van Nouhuys, D. Paluska, A. Richardson, S. Seung, M. Srinivasan, S. Strogatz, and N. Sydor.

Supporting Online Material
www.sciencemag.org/cgi/content/full/307/5712/1082/DC1
Materials and Methods
SOM Text
Movies S1 to S3
References and Notes

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SUPPORTING ONLINE MATERIAL
for
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This supporting material includes

1. **Materials and Methods.** Details about the robots' construction and control.

2. **An analogy.** A description of the parallels (in content, not in significance) between first powered flight and these robots.

In addition we hope readers will look at the videos:

S1 Cornell powered biped. This movie shows videos of the robot walking on flat ground. A slow-motion segment shows the ankle push-off actuation.

S2 Delft pneumatic biped. This movie shows the robot walking down a hall with views from the front, side, and back.

S3 MIT learning biped. This movie begins with the powered robot imitating passive walking down a 0.9 degree slope, from three camera angles. Then it shows the robot learning to walk on flat terrain with foam protective pads. The controller kicks the robot into random initial conditions between learning trials. After a few minutes, the robot is walking well in place, so we command it to walk in a circle. Finally, we show the robot walking down the hall, on tiles and outside; this footage is taken from a single trial where the robot adapted to each change in the terrain as it walked.

More material and other videos are available through
`http://tam.cornell.edu/~ruina/powerwalk.html`.

1 Materials and Methods

Details about the three robots are presented here.

1.1 Cornell powered biped.

This robot is autonomous; it has no power lines and no communication links to the outside. It consists of two 0.8 m long legs, each having knees, attached at a hip joint. The robot has curved-bottom

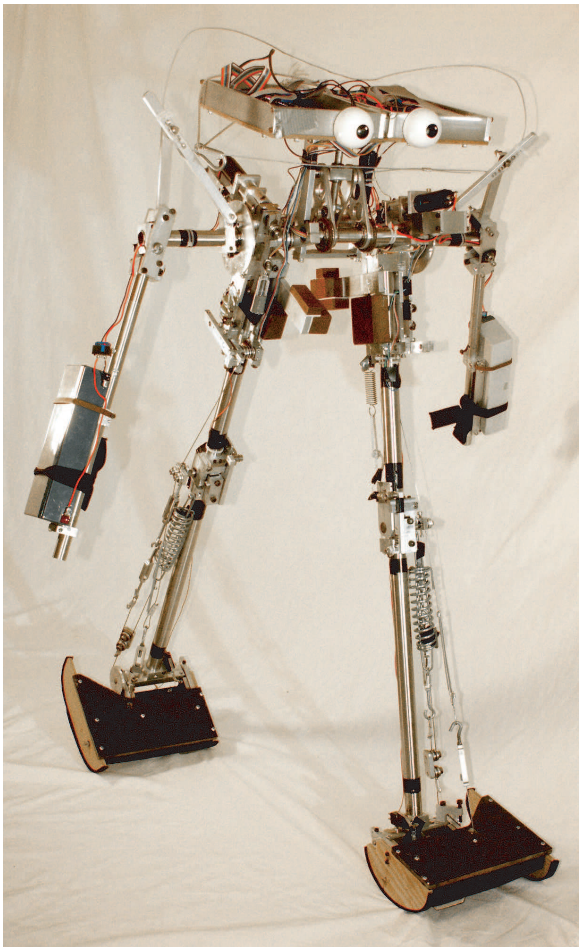

Figure 1: The Cornell powered biped

feet, arms, and a small torso which is kept upright by connection to the legs with an angle-bisecting mechanism. Each arm carries a battery. The right arm is rigidly attached to the left leg and *vice versa*, reducing yaw oscillations (Fallis, 1888, Collins, Wisse and Ruina 2001). The machine weighs 12.7 kg and has 5 internal degrees of freedom (one hip, two knees, and two ankles). The thigh-to-shank length and mass ratios are 0.91 to 1 and 3.3 to 1, respectively, which mimics human architecture and seems important to the passive dynamics of the system. The hip joint is fully passive. A latch at each knee passively locks the shank to be parallel with its proximal thigh throughout stance. This latch is released by a solenoid at the completion of ankle push-off, at which point the knee is passive until knee-strike. Ankle push-off restores energy lost, mostly to heel-strike collisions. To minimize the needed motor size, energy for ankle push-off is stored in a spring between steps.

The control circuitry is located in the hip/torso/head visible in the figure. A finite-state machine with eight binary inputs and outputs is implemented in 68 lines of code on an Atmel AT90S8515 chip running on an ATSTK500 standard development board. A second board with relays and passive conditioning components connects the board to the electromechanical and sensory parts. During the first state, Left Leg Swing, all actuators are unpowered and the left knee latch passively locks at knee strike. When ground-detection contact switches below the left foot detect impending heel strike, the state changes to Right Ankle Push-Off. This begins a timed activation of the solenoids that release the plantar-flexor spring of the right foot. When switches detect full foot extension, the state changes to Right Toe Return. During this state, a 9.5 Watt, 6.4 oz gear-reduced MicroMo® motor is activated, slowly retracting the foot and restoring spring energy. Also, a short time after detection of impending left-foot heel-strike, a solenoid unlocks the right knee. When a switch on the motor indicates full foot retraction, the state changes to Right Leg Swing, and the foot-retraction motor is deactivated. The state machine then swaps roles for the left and right legs and goes to the initial state. Taking all sensing, including the sensing of internal degrees of freedom (which could in principle be made open loop), about 20 bits of information per step flows to the processor. Environmental sensing, i.e., the instant of foot contact, is about seven bits per step.

This machine has only one capability, walking forward. It is designed to walk with minimal energy use. Its speed, path and joint motions are not shaped or controlled but follow from its mechanical design and primitive ankle push-off actuation. Ankle extension occurs mostly after the opposite leg has completed heel-strike collision, so in principle the machine could be made to consume about four times less energy by having ankle push-off before, rather than after, the opposing leg's foot-to-ground collision (Kuo, 2002). However, push-off before heel-strike seems to require more precise timing and also requires greater ankle torques. We surrendered this possible gain in energy effectiveness in trade for greater simplicity of control.

Low energy use was a primary goal in the design of the Cornell robot. We measured its power consumption during walking trials using an off-board digital oscilloscope connected with fine wires. At 500 samples per second, the scope measured battery voltage on one channel, and the voltage drop across a 1 ohm power resistor in series with the batteries on another. The product of the voltage and current was, on average, 11 watts (yielding $c_{et} = 0.2$). Mechanical energy use was measured in experimentally simulated push-off trials. The force at each foot contact point was measured as the ankle was slowly moved through its extension range, and this force was integrated to estimate mechanical work per step, yielding an average over a cycle of about 3 watts ($c_{mt} = 0.055$). This is a slight over-estimate of the mechanical energy used for propulsion because some energy is lost at the collision between the ankle and shank at full ankle extension.

The theoretical lower limit for the cost of transport in walking models is $c_{mt} = 0$. This can be achieved by swaying the upper body with springs in such a manner as to totally eliminate the collisional losses (Gomes and Ruina, 2005). Without swaying the upper body, a motion that would have significant energetic cost in humans, a rough lower bound on energetic cost can be estimated from the point-mass small-angle model of Ruina, Srinivasan and Bertram (2005) as

$$c_{et} \geq c_{mt} \geq J\frac{(d-d_f)^2}{\ell^2}\frac{v^2}{2gd} \approx 0.0003$$

where J is the collision reduction factor, which is 1/4 for push-off before heel-strike, $d \approx 0.4$m is the step length, $d_f \approx 0.2$m is the foot length, $\ell \approx 0.8$m is the leg length, $v = 0.4$m/s is the average velocity, and $g \approx 10$ m/s^2 is the gravity constant. In a dynamic 3-D model (adapted from Kuo 1999) with geometry, mass distribution, speed, and step length similar to this robot, without a hip spring or pre-emptive push-off, we found the mechanical cost of transport to be 0.013. Using the liberal collision reduction factor of 1/4 above, this yields a theoretical minimum of 0.003. Spring actuated leg swing, used by humans, could also significantly reduce the mechanical work requirements for walking at this speed by reducing step length. Thus, by a variety of estimates, the mechanical work of this robot walking at this speed, small as it is, seems to have room for an order of magnitude reduction.

The Cornell powered biped walked successfully during a period of a few weeks starting in July 2003. This robot is a proof-of-concept prototype, not a production-run machine. It was developed as a one-shot attempt using a small ($10K) budget. As is not unusual for experimental robots, the device did not stand up well to long periods of testing; on average about one mechanical component would break per day of testing. For instance, the cables connecting the motor to the primary ankle extension spring ran over a small radius pulley at the knee and broke frequently. When the Cornell robot was best tuned it would walk successfully at about 30% of attempts. Failed launches were due to inadequate matching of proper initial conditions, most often ending with foot scuff of the swing leg. The robot seems mildly unstable in heading, so once it was launched, the primary failure mode was walking off of the (narrow) walking table or walking into a wall. Uneven ground also lead to falls. Because it walked 10 or more steps many times, with the end only coming from hitting a wall or cliff, the gait is clearly stable (although not very) for both lateral and sagital balance. However, the reader can make his/her own judgments based on the videos which are the basic documentation of success.

A key aspect of the success, and also the touchiness, of this robot is the shape and construction of the feet. The general issues related to feet for this class of robots is discussed in Collins, Wisse and Ruina (2001). We tried various support-rail curve shapes and overall foot stiffnesses, and only one of these led to successful walking.

The Cornell machine, which uses wide supporting feet for lateral stability, is not being maintained. Rather, present efforts are aimed at developing a machine which uses simple active control for lateral balance using foot placement. This is used by humans during walking (Bauby and Kuo 2000) and the idea is related to the kinematic lean-to-steer mechanism of the Delft Biped and the steering used by a bicycle rider for balance.

1.2 Delft pneumatic biped

This robot is also autonomous; all power sources and computation are onboard. The robot weighs 8 kg, has 5 internal degrees of freedom (one hip, two knees, two skateboard-truck-like ankles), has an upper body, and stands 1.5 m tall. The swinging arms do not add degrees of freedom; they are mechanically linked to the opposing thighs with belts. The knees have mechanical stops to avoid hyperextension, and are locked with a controllable latch. Two antagonist pairs of air-actuated artificial muscles (McKibben muscles) provide a torque across the hip joint to power the walking motion.

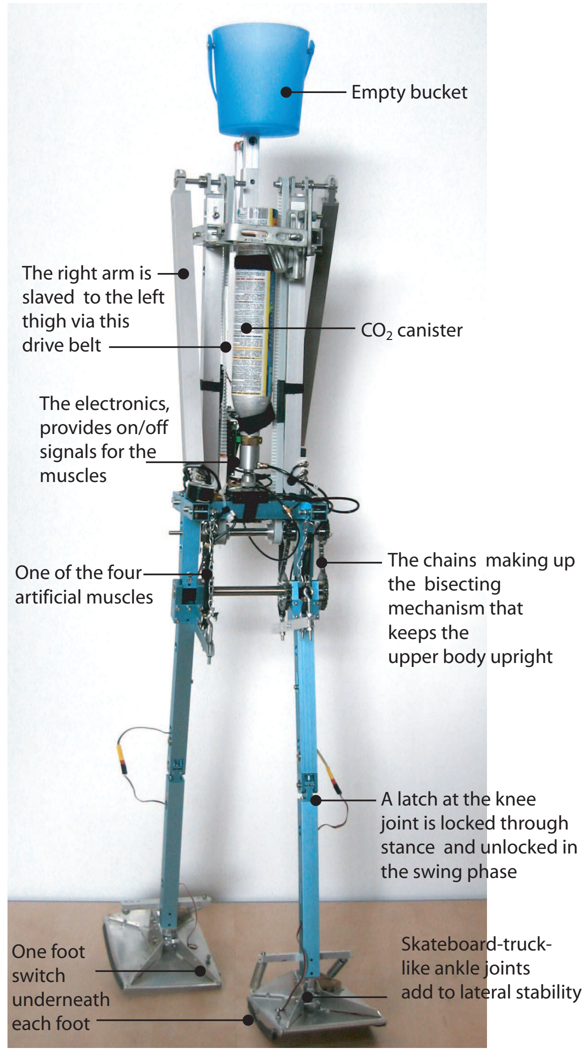

Figure 2: Delft pneumatic biped.

The muscles are fed with CO_2 from a 58 atm cannister, pressure-reduced in two steps to 6 atm through locally developed miniature pneumatics. Low-power, two-state valves from SMC Pneumatics® connect the artificial muscles either to the 6 atm supply pressure or to 0 atm. The calculation of $c_{mt} = 0.08$ for the Delft biped, used in the main paper, is based on actuator work (measuring the force-length relation of the muscles at the operating pressure). It does not take into account the huge (but inessential) losses from stepping down the gas pressure. To find a value for c_{et}, we calculated the decrease of *available energy* (or *exergy*) for a pressure drop from the 58 atm saturated liquid state to atmospheric pressure. Available energy represents the amount of work that could be done with the pressurized gas if the both the gas expansion process and the simultaneous heat transfer process are reversible (i.e. lossless). In that hypothetical setting, one can use the enthalpy and entropy values for the gas at the beginning and the end of the expansion process. At a constant temperature of 290 K, this amounts to a loss of available energy of 664 kJ per kg CO_2. A 0.45 kg canister can power the 8 kg robot for 30 min of walking at 0.4 m/s yielding c_{et} = 5.3. This value has little meaning, however. First, even the best real-world gas-expansion systems can only use about 30% of the theoretically available energy, due to irreversibility issues. More importantly, most of the expansion loss would be eliminated if the CO_2 had been stored at 6 atm. Unfortunately this would require an impractically large storage tank. Thus the discrepancy between c_{et} = 5.3 and c_{mt} = 0.08 is due to practical problems associated with using compressed-gas energy storage.

McKibben muscles have a low stiffness when unactuated, leaving the joints to behave almost passively at zero pressure. At higher pressures, the McKibben muscles behave as progressively stiffer springs. By activating opposing muscles in different proportions, the relaxed angle of a joint can be controlled. This is applied at the hip where the artificial muscles alternate in action. At the start of each step, determined by a foot switch, one muscle is set to 6 atm and the other to 0 atm. The swing leg is thus accelerated forward until the relaxed angle of the hip is reached, where it (approximately) stays due to damping in the muscles and in the joint. If sufficient hip joint stiffness is obtained from the hip muscles, stable walking similar to that of McGeer's four-legged machine can be obtained. The upper body is kept upright via a kinematic restriction, a chain mechanism at the hip which confines the upper body to the bisection angle of the two legs (Wisse, Hobbelen and Schwab, 2005).

Lateral stability in two-legged robots can be obtained in a number of ways (Kuo, 1999), and one solution was tested in the Delft robot. The feet are attached to the lower leg via special ankle joints (Wisse and Schwab, 2005) which have a joint axis that runs from above the heel down through the middle of the foot, quite unlike the human ankle but much like skateboard trucks. The mechanism creates a nonholonomic constraint, which can enable stability without dissipation, as found in skateboards (Hubbard, 1979). If the robot starts to lean sideways as a result of a disturbance, the ankle allows the foot to remain flat on the floor. Due to the tilted joint orientation, the leaning is accompanied by steering. If the walker has sufficient forward velocity, this steering helps prevent it from falling sideways, much like the turning of a bike wheel into a fall helps prevent a bike from falling down.

A Universal Processor Board from Multi Motions® (based on the Microchip® PIC16F877 micro-controller) uses foot-contact switch signals to open or close the pneumatic valves. The control program is a state machine with two states: either the left or the right leg is in swing phase. At the beginning of the swing phase, the swing knee is bent. Four hundred milliseconds after the start of the swing phase, the knee latch is closed, waiting for the lower leg to reach full extension through its passive swing motion. Programmed in assembly, this amounts to about 30 lines of code. The only sensing is the time of foot contact, used once per step. Taking account of the implicit rounding from the processor loop time, we estimate the sensor information flow rate is about six bits per second.

The Delft powered biped first walked successfully in July 2004. When mechanically sound, most of the manual launches (by an experienced person) result in a steady walk. Falls can often be attributed to disturbances from within the machine (a contact switch that performs unreliably, or a cable that gets stuck between parts), and occasionally to floor irregularities. Another problem is that the pneumatic and mechanical systems (which were developed at Delft for a proof-of-principle prototype rather than an industrial-strength product) have frequent mechanical failures that often need a day or more to fix. At present the machine is being kept working so it can repeat the behavior shown in movie S2.

1.3 MIT learning biped.

First we duplicated the Wilson design (Fig. 1a of the main paper) using two rigid bodies connected by a simple hinge. The kneeless morphology was

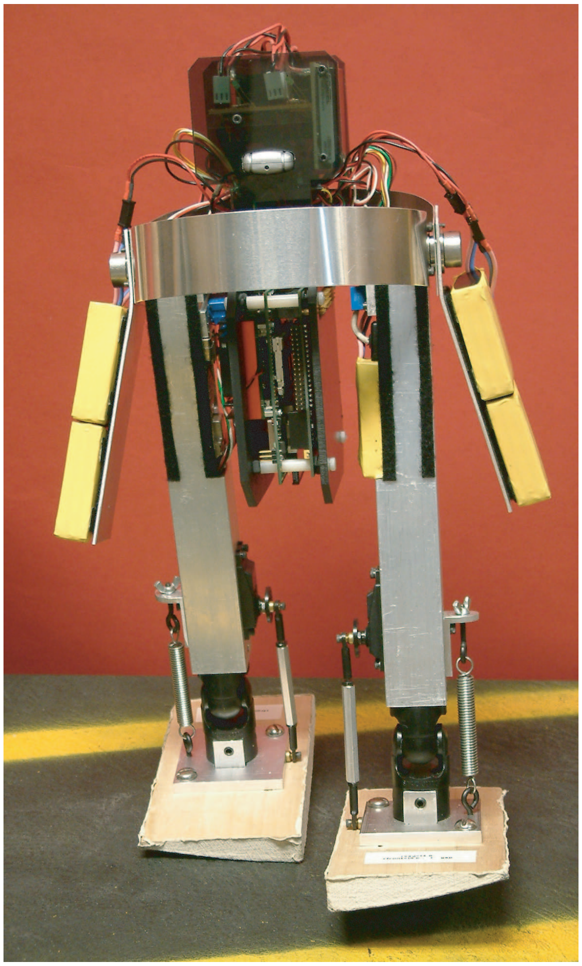

Figure 3: The MIT learning biped

chosen to reduce the number of joints and actuators on the robot, minimizing the combinatorial explosion of states and control strategies that the learning algorithm needed to consider. The gait was iteratively improved in simulation by changing the foot shape for a given leg length, hip width, and mass distribution. The resulting ramp-walker (Fig. 1b of main paper) walks smoothly down a variety of slopes. The powered version uses tilt sensors, rate gyros, and potentiometers at each joint to estimate the robot's state, and servo motors to actuate the ankles. The completed robot weighs 2.75 kg, is 43cm tall, and has 6 internal degrees of freedom (each leg has one at the hip and two at the ankle). Before adding power or control, we verified that this robot could walk stably downhill with the ankle joints locked.

The robot's control code runs at 200Hz on an embedded PC-104 Linux computer. The robot runs autonomously; the computer and motors are powered by lithium-polymer battery packs, and communication is provided by wireless ethernet. This communication allows us to start and stop the robot remotely; all of the control algorithms are run on the onboard computer.

The learning controller, represented using a linear combination of local nonlinear basis functions, takes the body angle and angular velocity as inputs and generates target angles for the ankle servo motors as outputs. The learning cost function quadratically penalizes deviation from the dead-beat controller on the return map, evaluated at the point where the robot transfers support from the left foot to the right foot. Eligibility was accumulated evenly over each step, and discounted heavily ($\gamma \leq 0.2$) between steps. The learning algorithm also constructs a coarse estimate of the value function, using a function approximator with only angular velocity as input and the expected reward as output. This function was evaluated and updated at each crossing of the return map.

Before learning, outputs of both the control policy and the value estimate were zero everywhere regardless of the inputs, and the robot was able to walk stably down a ramp; because it is simulating passive-dynamic walking, this controller runs out of energy when walking on a level surface. The robot kicks itself into a random starting position using a hand-designed control script to initialize the learning trials. The learning algorithm quickly and reliably finds a controller to stabilize the desired gait on level terrain. Without the value estimate, learning was extremely slow. After a learning trial, if we reset the policy parameters and leave the value estimate parameters intact, then on the next trial the learning system obtains good performance in just a few steps, and converges in about two minutes.

The resulting controller outputs ankle commands that are a simple, time-independent function of the state of the robot, and does not require any dynamic models. All learning trials were carried out on the physical biped with no offline simulations. The learned controller is quantifiably (using the eigenvalues of the return map) more stable than any controller we were able to design by hand, and recovers from most perturbations in as little as one step. The robot continually learns and adapts to the terrain as it walks.

The MIT biped, which was not optimized for energy efficiency, has $c_{et} = 10.5$, as calculated by the energy put back into the batteries by the recharger after 30 minutes of walking. The c_{et} for this robot is especially high because the robot has a powerful computer (700 MHz Pentium) on a light robot that walks slowly.

The version of the MIT powered biped shown here first walked successfully in January 2004. The earliest powered prototype of this type at MIT first walked successfully in June 2003.

The MIT biped is still working well, and is the subject of active development and study. New learning algorithms and new design elements (such as different curvatures in the feet) are being tested with the same hardware. A new version with knees is mostly developed. The robot has walked for a few one-hour on-the-treadmill energy-use trials (the batteries would have lasted for about 90-100 minutes).

2 Analogy with first powered flight*

On December 17, 1903 the Wright brothers first flew a heavier-than-air man-carrying powered machine. There are various parallels between their machine and the simply-powered low-energy-use walking robots described here.

Starting from before the work began, the Wright's were inspired by flying toys. The walking machines here were also inspired by, and even partially based on, walking toys.

The Wright's ideas about control of steer in aircraft were based on the relation between steer and lean in bicycles. Our research in the passive balance of robots was inspired by the self-stability of bicycles.

The Wrights worked for years developing gliders, planes powered by the release of gravitational potential energy as they flew down a glide slope. This was in contradiction to a common paradigm of the time, which was to try to get a powered plane to work, motor and all, all at once. Once they had mastered gliding they were confident they could master powered flight. On the second day they tried the idea, adding a primitive engine to a glider design, they made their famous flight. Our development of passive-dynamic walkers, robots that walk down gentle slopes powered only by gravity, was by far the bulk of our efforts. Once we had those working well we were confident that the machines could walk on the level with a small addition of power. The result that adding power to a downhill machine works is one of the subjects of this paper.

The analogy above is not accidental. Tad McGeer, the pioneer of passive-dynamic robotics, was trained as an aeronautical engineer. McGeer's foray into robotics was directly and explicitly an imitation of the Wright Brothers paradigm. It worked for the Wrights after others failed at mastering power and flight all at once. Perhaps, McGeer thought, it could work for the more pedestrian task of making an efficient walking robot. McGeer put aside the project after making significant progress with passive machines (walking robot gliders), returning to the world of airplane design. Our research has been, more or less, to pick up where McGeer left off, improve the 'gliders', and then add simple power.

* The analogy has its limits. Heavier-than-air powered flight was a well-defined major goal over a long period of time with huge consequences. That

accomplishment swamps anything that might happen with robotics, including this research. The Wright analogy does not extend to the significance of our work, which is hugely less.

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