The Evolution of Control and Adaptation in a 3D Powered Passive Dynamic Walker

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Abstract

Humans demonstrate speed, efficiency, and adaptability when traveling over rugged terrain. Bipedal robots modeled on biological designs could replace or assist people working in difficult environments. However, current research into humanoid robots has not produced practical machines. This paper explores the use of evolutionary robotics to evolve a simulation of a ten-degree of freedom bipedal robot. This machine demonstrates many of the properties of human locomotion. By using passive dynamics and compliant tendons it conserves energy while walking on a flat surface. Its speed and gait can be dynamically adjusted and it is capable of adapting to discrepancies in both its environment and its bodies' construction.

Introduction

The development of bipedal machines could allow robots to replace or assist humans in dangerous occupations such as firefighting, bomb disposal, and reconnaissance. Traditionally these kinds of tasks involve rugged environments such as forested, mountainous, and urban terrain, which are challenging for wheeled and tracked vehicles. While people demonstrate dynamic, efficient, and adaptable locomotion in these environments, bipedal robots have demonstrated few of these qualities. Some of these issues may be a result of the differences between biological approaches and technological ones. People have analog nervous systems that are highly parallel, while modern technology is based on deterministic digital computers. Humans are reactive and dynamic, while traditional artificial intelligence is based on linear ideas like: sense, plan, and act (Brooks, 1991). To develop machines with similar properties to humans, it is reasonable to assume they might need to have similar designs. One of the reasons human locomotion is so efficient is that it leverages passive dynamics to reduce energy consumption and uses the elastic nature of tendons to store and release energy. When electrodes are placed in the leg muscles of humans they show almost no activity in the swing leg during walking, except at the beginning and the end of the swing phase (Basmajian, 1976). This is because muscles initiate each step and then allow the stepping leg to swing passively past the stance leg. To determine how much energy can be attributed to tendons, Biewener and Blickhan (1988) recorded the amount of force horses feet exerted when they ran on force plates. They estimated that during galloping the forces released by the tendons recoil contributed to up to 40% of the positive work. Human locomotion is not only efficient but it can also dynamically adapt to changes in environment such as the ruggedness of terrain and even to anomalies in the body due to injury or disabilities. This is accomplished through pulsating collections of neurons called central pattern generators (CPG) in the spine. A CPG is used to generate different gaits that are later modulated by sensors in the muscles and tendons (Grillner, 2003). Through sensor feedback and plasticity the human gait can adapt to both external and internal influences.

This paper explores an approach to bipedal walking that is more closely based on biological designs. Through the use of evolutionary robotics techniques we evolve a simulated bipedal machine that is dynamic, efficient, and adaptable. In our model the body and control system form a single dynamic system whose basin of attraction is walking. Neural networks are used for control, passive dynamics for efficiency, and a CPG to initiate and regulate the walking gait. The result is a simulated machine with ten-degrees of freedom that embodies many of the characteristics of humanoid walking. Its gait and speed can be controlled dynamically, it has a passive swing-leg, and it can adapt to both external and internal disturbances.

Previous work and background

Evolutionary robotics is the use of biologically inspired techniques such as artificial neural networks and genetic algorithms to evolve the morphology and control systems of robots. We see these as dynamic systems whose basin of attraction is the performance of a specific behavior. When a machine enters a situation not encountered during evolution, the attractor will often pull the machine back into stability (Harvey et al., 1996). In 2003 we used evolutionary robotics techniques to evolve both two and three-dimensional passive dynamic walkers. These machines were powered on a flat surface using only their ankles and simple neural networks. Experiments revealed that passive dynamic walkers could have multiple knees as well as having a natural robustness to external noise (Vaughan, 2003).

In 1998 Honda developed a humanoid android P3 (Hirai et al., 1998) and later a smaller machine Asimo. These machines were bipedal and had 12 degrees of freedom in the legs. While they demonstrated the ability to ascend stairs and adapt to subtle slope changes they did not make use of tendons or passive dynamics. This resulted in unnatural walking that was both slow and inefficient.

At MIT a bipedal robot simulation M2 was created with 12 degrees of freedom (Pratt and Pratt, 1999). It had passive leg swing and used actuators that mimicked tendons and muscles. Its control system was composed of a series of hand written dynamic control algorithms. A genetic algorithm was used to carefully tune the machines parameters. When constructed physically this machine was never observed to walk. This may have been the result of discrepancies between the simulation and the physical robot. In our model we aim to resolve this by demonstrating the ability to adapt dynamically to anomalies in the body.

McGeer (McGeer, 1990) designed and simulated a two-dimensional bipedal passive dynamic walker (PDW) with knee joints and curved feet. By carefully selecting the leg mass, leg length, and foot size this robot was able to walk down a four-degree slope with no motors and no control system *(Figure 1)*. Endo (Endo et al., 2002) attached neural oscillators to the joints of a simulated two-dimensional biped, which successfully walked on a flat surface. Bongard (Bongard and Paul, 2001) used evolutionary robotics techniques to evolve the body and control system of a simulated bipedal walker. Their machine had six degrees of freedom and spherical feet. Collins (Collins et al., 2001) physically built a three-dimensional PDW that walked a three-degree slope. The estimated amount of potential energy used by their walker was only three watts.

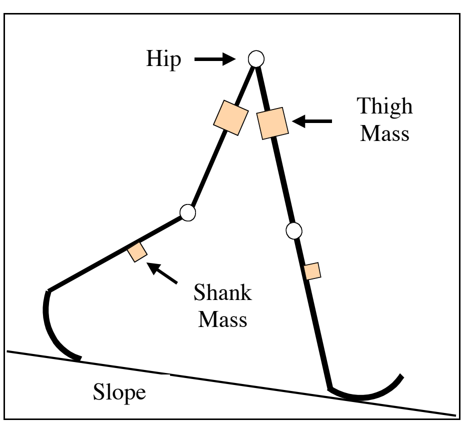

Figure 1: A passive dynamic walker

The simulation

The body of our simulated machine had ten-degrees of freedom: two at each hip, one at each knee, and two at each ankle *(Figure 2)*.

The physics of the body were simulated using the open

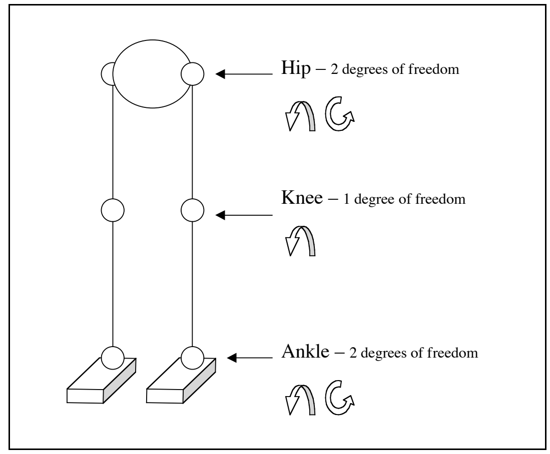

Figure 2: Degrees of freedom in the body

dynamics engine (ODE) physics simulator (Smith, 2003). Weights and measures were computed in meters and kilograms and gravity was set to earths constant of 9.81. The body on average was one meter tall and had 17 parameters *(Figure 3)*: M_w is the mass of waist, M_t is the mass of thigh, M_s is the mass of shank, M_f is the mass of foot, L is the length of a leg segment, Y_t is the offset of the thigh mass on the y-axis, Y_s it the offset of shank mass on y-axis. X_t is the offset of the thigh mass on the x-axis, X_s is the offset of shank mass on x-axis, L_f is the length of foot, A_x is the ankle spring/damper around x-axis, K_x is the knee spring/damper around x-axis, H_x is the hip spring/damper around the x-axis, W is the radius of the waist, B_y is the starting angle of hips joint around y-axis, H_y is the spring/damper of hip around y-axis, A_y is the ankle spring and damper around the y-axis. Parameter ranges were selected based on observations of the human body. The mass of the foot was restricted to be less than that of the shank, the mass of the shank was less than that of the thigh, etc. All parameters were encoded in the genome.

The PDWs explored by McGeer (McGeer, 1990) had curved rigid feet. However, humans have relatively flat feet with ankles. This allows them to increase their traction and stability by keeping more of their foot surface on the ground. The ankle acts as a lever to inject energy in the gait as well as storing and releasing energy through compliant tendons. The PDW developed by Collins (Collins et al., 2001) using curved feet tended to pivot on each step decreasing stability. Kuo (Kuo, 1999) found a similar problem when exploring the lateral stability of a three dimensional straight-legged passive dynamic walker. The addition of roll motion created

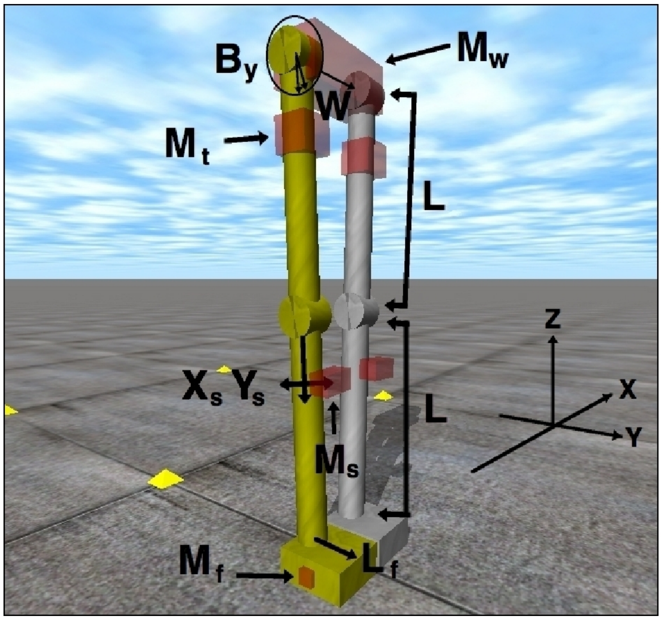

Figure 3: Illustration of body parameters

unstable modes in the periodic gait causing it to fall to one side or the other. We addressed this issue by using ankles and flat feet to increase traction. *(Figure 4)*.

In the human leg, muscle spindles and golgi tendon or-

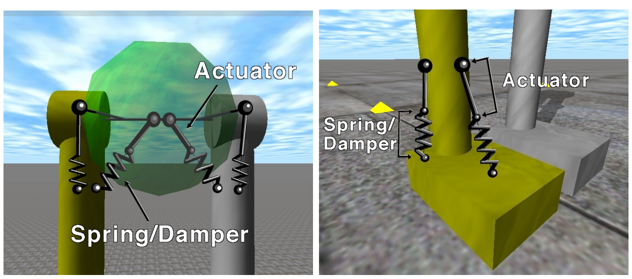

Figure 4: Springs and dampers in the hips and ankles

gans are used to sense the angle and relative forces placed on them (Alexander, 2002). Through this mechanism they can dynamically adjust their movement. To simulate compliant tendons each joint was composed of a linear actuator that was attached to a spring/damper similar to the series elastic actuators found in MITs M2 (Pratt and Pratt, 1999). Angle sensors on the joint and deflection sensors on the spring/damper were used to acquire feedback *(Figure 4)*.

Almost all life on earth is symmetric, either radial (starfish) or bilateral (insects, mammals, and reptiles) (Miller and Levine, 1998). Even the human brain is symmetrically divided between left and right hemispheres. To explore whether independent neural networks without synaptic coupling can coordinate to produce walking, we used two symmetric networks and attached one to each leg *(Figure 5)*.

The walking gaits in frogs are generated in the spinal column and then transformed into force patterns that direct their limbs to an equilibrium point in space (Bizzi et al., 1995). In the Lamprey the spinal column is composed of segments each with local touch sensors that modulate its rhythmic swim gaits (Grillner, 2003). In our model we created a virtual spinal cord of neurons that run down each leg. The cord was segmented into three sections one for each joint *(Figure 6)*. Each segment contained two hidden neurons for each degree of freedom that were connected to local sensors for detecting the angle and forces applied to the joint. To power them, a symmetric central pattern generator was attached that sent alternating pulses of opposing signs to each network. There were no axons between the two networks so their only method of communication and interaction was through the bodys actuators and sensors.

Humans have an inner ear with three semicircular canals. They allow people to detect orientation as well as acceleration changes. To mimic this mechanism, a group of three simulated gyroscopes and accelerometers around the x, y, and z-axes were attached to the neural network. To reduce the search space the wiring between sensors and motor neurons was not fully connected. MIT's M2 (Pratt and Pratt, 1999) robot placed a strict separation between the control systems for lateral motion (x-axis) and forward motion (y-axis) and demonstrated natural dynamic walking. In our model we have made a similar design decision. In general sensors around or along one axis were connected to the corresponding motor neurons for the same axises. To give the networks symmetric behavior the sign of the inputs and outputs along the x-axis were inverted in one of the networks. To ensure the default behavior of the ankles and hips was to return to a zero degree angle, negative connections were placed directly between some sensors and motor neurons: specifically between the hips rotating around the y axis and the ankles rotating around the x axis. *(Figure 6)*

Feed-forward continuous time neural networks (CTNN)

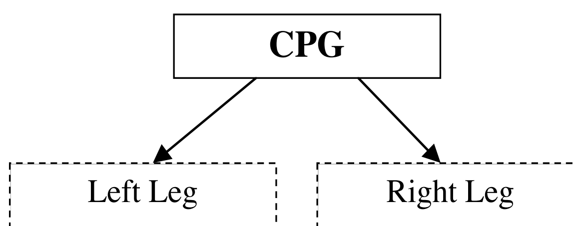

Figure 5: Symmetrical neural networks. The CPG sends pulses to two identical networks one for the left leg and one for the right.

were used to add power to the machine. Unlike traditional neural networks, a CTNN uses time constants to allow neu-

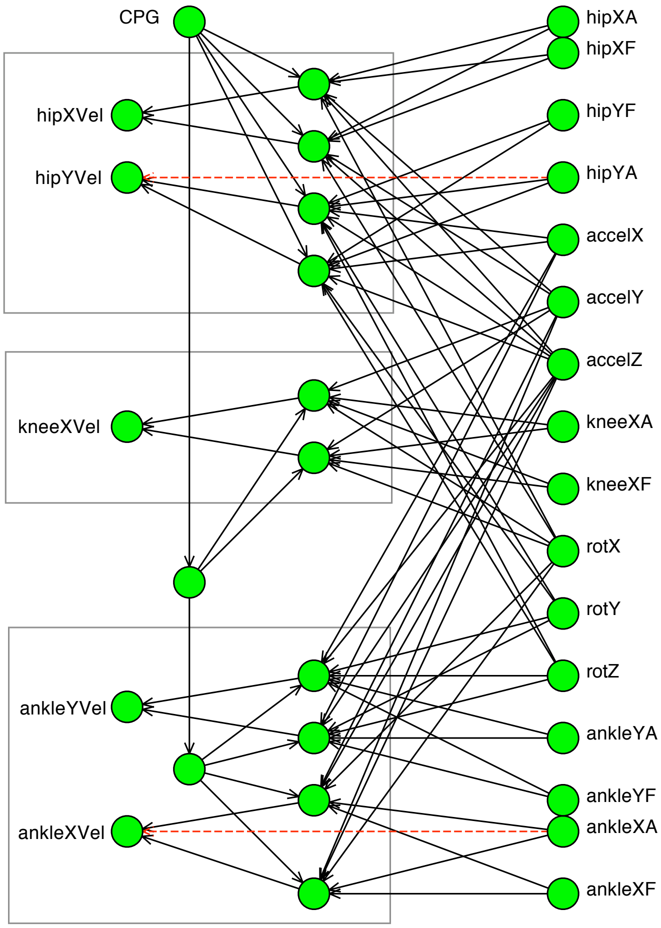

Figure 6: Detail of neural network. Segments are enclosed in boxes. Outputs are on the left and inputs are on the right. 'X', 'Y', or 'Z' are rotation around an axis. Accelerometers 'accel' are a special case where 'X','Y','Z' is acceleration along the axis. 'A' is an angle sensor and 'F' is a force sensor (i.e deflection of spring). 'Vel' is the desired velocity of the output motor. Dotted lines indicate a negative weight and solid lines indicate either a positive or negative weight. All weights were encoded in the genome.

rons to activate in real time and out of phase with each other. For a detailed analysis of this kind of network refer to (Beer, 1996). The state of a single neuron was computed by the following equation:

$$\tau_i \dot{y}_i = -y_i + \left[\sum_{j=1}^{N} w_{ji}\sigma(g_j(y_j))\right] + I_i + \Omega \qquad (1)$$

Where y is the state of each neuron, τ is a time constant, w is the weight of an incoming connection, σ is the sigmoid activation function tanh(), g is the gain, I is an external input, Ω is a small amount of Gaussian noise in the range of [-0.0001, 0.0001]. The state of each neuron was integrated with a time step of 0.2 using the Euler method. In our model neurons were encoded in the genome with τ and g while axons were encoded with real values in the range of [-5, +5]. Biases were omitted.

Four islands (Whitley et al., 1999) of a geographically distributed genetic algorithm (Husbands, 1994) were used each with a population of 50 individuals. The mutation rate was set to 0.5 and then lowered slowly during evolution. Crossover was random. This kind of evolutionary algorithm was used as it has proved previously effective in this context but we do not discount other algorithms being equally effective.

Walking

As demonstrated by Basmajian (1976), the human body takes advantage of passive dynamics during walking. A good question to ask is whether a CPG can initiate walking in a PDW. To find out, the body and control system of a PDW was evolved. The machine was placed on a four-degree incline and the CPG was turned on. Upon completion of a single step the network was completely disconnected from the machine and the ankle actuator was powered back to 0 degrees where it stayed fixed for the duration of the simulation. The fitness function was:

$$f = d\left(\frac{1}{1+t}\right)\left(\frac{1}{1+x}\right)\left(\frac{1}{1+z}\right)\left(\frac{1}{1+r}\right)\left(\frac{1}{1+y}\right) \qquad (2)$$

Where: f is the fitness, d is distance travelled, t is the torque used, x is rotation of hip around the x-axis, z is the acceleration of the hip along the z dimension, r is rotation of feet around the z-axis, y is the rotation of the hip around the y-axis. t, x, z, r, and y were averages taken over the entire evaluation time. This fitness function was chosen because it selects for machines that walk as far and straight as possible without explicitly specifying how they move their legs. This allows their leg trajectories to emerge from the dynamics of their bodies rather than from the observations of a human gait. The result was a machine that passively walked down a four-degree slope *(Figure 7)*.

Central pattern generators in animals often dynamically change their rhythm. This can be seen when animals move from one gait to another or wish to increase or decrease their speed. In order to achieve this, the neural networks in our system must be responsive to the pulses of the CPG. If the network in figure 6 is used without any changes it is possible for the machine to walk by ignoring the CPG and setting up a feedback loop with its sensors. This is called a reflexive pattern generator (Beer, 1995) and has been successfully used to power passive dynamic walkers on a flat surface when little or no control of the gait is required (Vaughan, 2003). What is needed is to initially evolve a network with an attractor that is sensitive to the CPG and then allow the sensors to modulate its activity. To do this a subsumption approach was taken. Popularized by Brooks (Brooks, 1991) the idea is to first build and test a simple system and then add additional systems on top. To implement this in our model, first the network was evolved without sensor feedback and

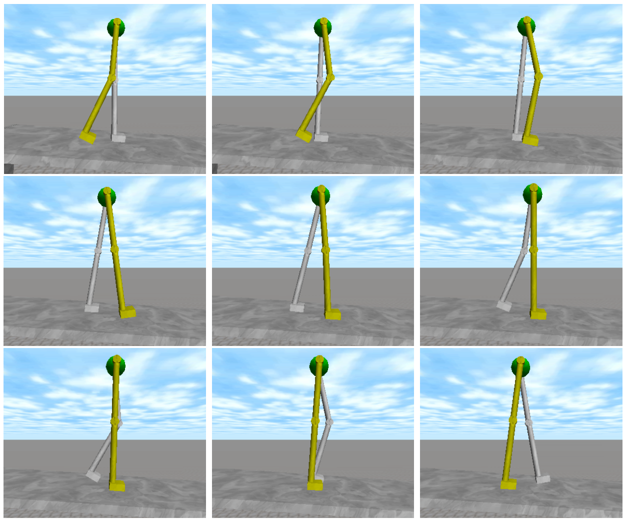

Figure 7: The gait of the passive dynamic walker unpowered on a four-degree slope.

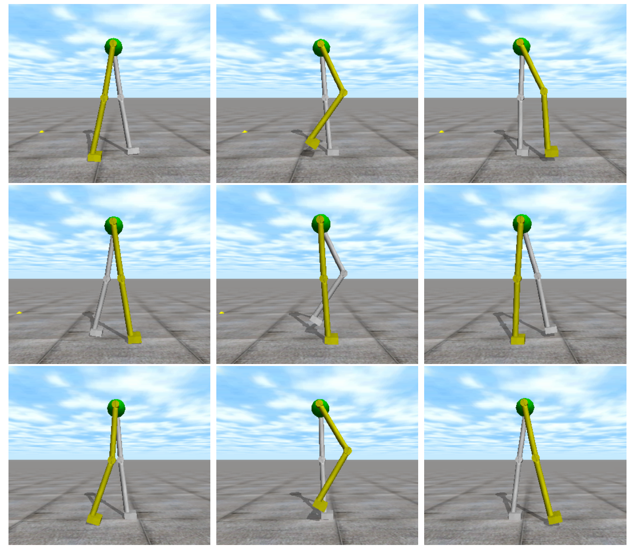

Figure 8: Gait of powered walker on a flat surface.

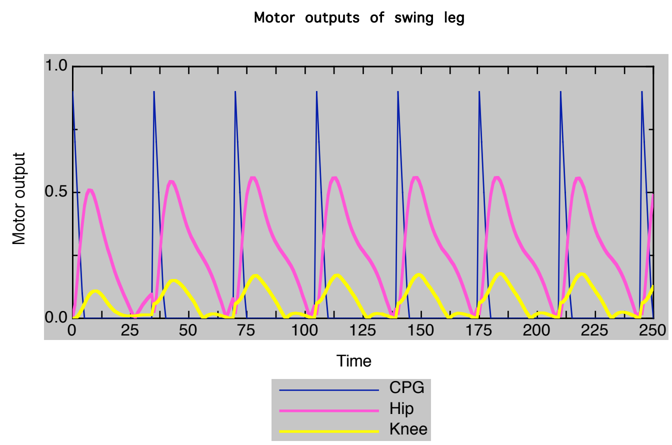

Figure 9: Graph of hip and knee motor outputs on the swing leg while walking on a flat surface. The graph of the knee motor indicates passive swing toward the the end of the swing phase.

then later sensors were reconnected to ensure the system was sensitive to the CPG. The fitness function was modified by multiplying it by the additional factor $\frac{1}{1+v}$ where v is the difference between the powered and passive machines average velocity. The timing of foot strike was recorded from the passive walker and the CPG was updated to pulse with the same timing. The machine was placed on a four-degree slope and the connections to all sensors except those with negative feedback were removed from the network. An oscillating rhythm was applied and the machine was evolved to walk powered down the inclined platform. Once the machine walked for more than ten steps the axons were reconnected to their sensors with very small weights and the population was evolved for an additional number of generations. Over hundreds of generations the slope was incrementally lowered from a four-degree slope to a flat surface. The result was a dynamically stable machine that was not observed to fall even after thousands of steps *(Figure 8)*.

The passive dynamic nature of the machine was preserved. Observation of the motor neurons revealed an increased activity at the start of a step and then a decrease in activity in the swing leg. This is illustrated in *(Figure 9)*. At the start of a pulse both the hip and knee motors are activated. For the first half of the swing phase the knee is extended but on the second half it is nearly turned off to allow it to passively swing past the stance leg.

Robustness

Animals are very adaptive to environmental changes. If the ruggedness of the ground changes suddenly they can dynamically adjust their gait to regain equilibrium. If they are injured or are born with physical abnormalities their body and gait adapts. They do this through the plasticity of their motor neurons as well as feedback loops between muscles and sensors. To determine the extent evolution can shape the body and control system to cope with noise, the same machine was evolved for an additional 100 generations. On each evaluation small force vectors along the x, y, and z-axis in a Gaussian distribution were applied. The result was a machine that developed dynamic mechanisms to adapt to noise. When pushed too far to one side, the machine was observed to adjust its foot placement by stepping inward to regain balance *(Figure 10)*.

A second experiment was to try to determine the machines ability to adapt to internal noise. The previous experiment was repeated except this time the random forces were replaced by mistakes in the body's construction. Each time the machine was built, errors were introduced to all body

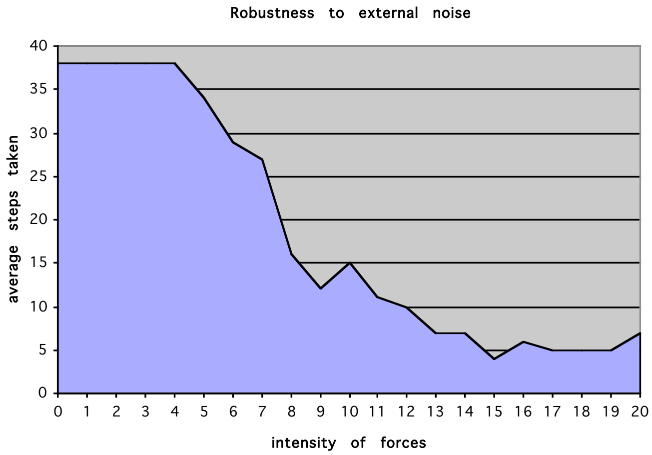

Figure 10: The y-axis is the average number of steps taken over 10 trials and the x-axis the magnitude of forces applied in a Gaussian distribution. Steps were capped at 38.

parameters. The result was a machine that even when built incorrectly could still walk in simulation *(Figures 11 and 12)*.

This result is very important because it demonstrates that

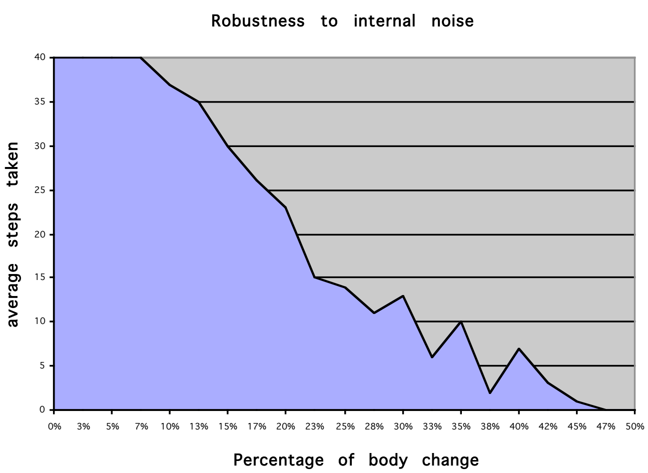

Figure 11: Robustness to internal noise. The y-axis is the average number of steps taken over 20 trials and the x-axis is the amount of noise in construction taken as a percent. (i.e. 10 would be a 10% random change in the overall size of a parameter). Steps were capped at 40.

a control system based on feedback can adapt to changes in the body. It also provides a possible solution to a long-standing problem with robotic simulations. When a simulated control system is transferred to a physical robot, it often fails because it did not take into account small differences between the simulation and reality. Our control system on the other hand appears to compensate by using feedback with its sensors and can adjust to changes dynamically. Even with a 20% error in all body parameters this machine

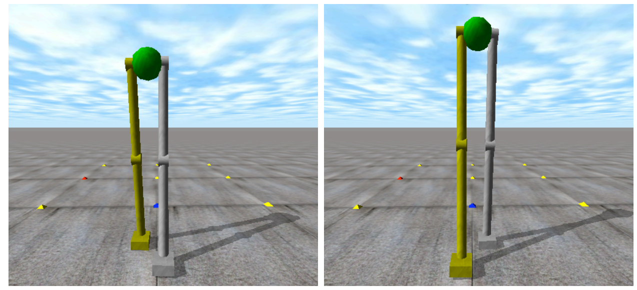

Figure 12: Two different bodies that walk with the same control system.

still manages to take on average 25 steps. This adaptability may increase its likelihood of making the transfer to a physical robot.

The walking attractor intentionally evolved before the sensors were reconnected continued to be responsive to the CPG. When the time between the CPGs pulses was reduced or increased the machine slowly adjusted its gait to line back up with the new pulse timing *(Figure 13)*. This not only demonstrates that the machines attractor can adapt to situations not experienced during evolution, but it also provides a possible mechanism for controlling the machines speed or changing its gait.

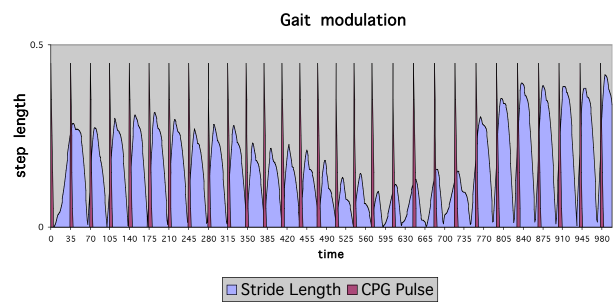

Figure 13: After the first 8 steps the CPG pulse rate is decreased slightly causing the machine to take smaller steps. On step 16 the rate is increased causing the machine to take larger steps.

Conclusion

Humans demonstrate dynamic, efficient, and adaptable locomotion. This is accomplished by the combination of passive dynamics, sensor feedback, and central pattern generators in the spine. These mechanisms are highly parallel and quite different from traditional artificial intelligence approaches. By applying techniques based closer on biological principles such as evolutionary robotics we have demonstrated that it is possible to build dynamic, efficient, and adaptable robots. Instead of a control system based on a linear program a parallel attractor was evolved to keep the machine in a walking gait. Control was decentralized into two symmetrical networks that demonstrated coordinated walking despite the fact there was no direct communication between them. Passive dynamic leg swing was observed indicating that physical machines based on this model could be energy efficient. Through manipulation of the CPGs rhythms the speed of these machines could be adjusted dynamically providing a form of external control. In the future this mechanism may also be used to change the gait between walking and running. The machines attractor was shown to dynamically adapt to both external and internal environmental changes. This is an interesting result since the CTNNs of our model do not store information through weight changes, as many conventional artificial neural networks do. Instead it had to rely entirely on the feedback between its sensors and actuators. This adaptability may provide a mechanism for transferring simulated control systems to physical robots.

This technique is very powerful and we are currently using it to explore more complex bipedal machines with torsos and spines. Some of these simulated machines have up to 25 degrees of freedom and have demonstrated the ability to dynamically run. We are now beginning to build a physical android based on this model and hope to discover further insights into how to use these methods to develop practical bipedal machines. Videos of our simulated machines can be found at (www.droidlogic.com).

References

Alexander, R. (2002). *Principles of Animal Locomotion.* Princeton University Press, New Jersey.

Basmajian, J., V. (1976). The human bicycle. *Biomechanics*, 3-A.

Beer, Randal, D. (1995). A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence*, 72:173-215.

Beer, Randal, D. (1996). Toward the evolution of dynamical neural networks for minimally cognitive behavior. In Maes, P., Mataric, M., Meyer, J., Pollack, J., and Wilson, S., editors, *From animals to animats 4: Proceedings of the Fourth International Conference on Simulation of Adaptive Behavior*, pages 421–429. MIT Press.

Bizzi, E., Giszter, S. F., Loeb, E., Mussaivaldi, F. A., and Saltiel, P. (1995). Modular organization of motor behavior in the frog's spinal-cord. *Trends In Neurosciences*, 18:442–446.

Bongard, J. C. and Paul, C. (2001). Making evolution an offer it can't refuse: Morphology and the extradimensional bypass. In Keleman, J. and Sosik, P., editors, *Proceedings of the Sixth European Conference on Artificial Life, Prague, CZ*, pages 401–412.

Brooks, R. A. (1991). Intelligence without representation. *Artificial Intelligence*, 47:139–159.

Collins, S. H., Wisse, M., and Ruina, A. (2001). Passive dynamic walking robot with two legs and knees. *The International Journal of Robotics Research*, 20(7):607–615.

Endo, I., Yamasaki, F., Maeno, T., and Kitano, H. (2002). A method for co-evolving morphology and walking patterns of biped humanoid robot. In *Proceedings of the IEEE Conference on Robotics and Automation*.

Grillner, S. (2003). The motor infrastructure: From ion channels to neuronal networks. *Nature Reviews Neuroscience*, 4(7):573–586.

Harvey, I., Husbands, P., Cliff, D., Thompson, A., and Jakobi, N. (1996). Evolutionary robotics: The sussex approach. *Robotics and Autonomous Systems*, 20:205–224.

Hirai, K., Hirose, M., Haikawa, Y., and Takenaka, T. (1998). The development of the honda humanoid robot. In *IEEE Int. Conf. Robotics and Automation*, pages 1321–1326.

Husbands, P. (1994). Distributed coevolutionary genetic algorithms for multi-criteria and multi-constraint optimisation. In Fogarty, T., editor, *Evolutionary Computing, AISB Workshop Selected Papers*, volume 865 (LNCS), pages 150–165. Springer-Verlag.

Kuo, A. D. (1999). Stabilization of lateral motion in passive dynamic walking. *International Journal of Robotics Research*, 18(9):917–930.

McGeer, T. (1990). Passive walking with knees. In *Proceedings of the IEEE Conference on Robotics and Automation*, volume 2, pages 1640–1645.

Miller and Levine (1998). *Biology*, chapter 26, page 662. Prentice Hall.

Pratt, J. and Pratt, G. (1999). Exploiting natural dynamics in the control of a 3d bipedal walking simulation. In *Proceedings of the International Conference on Climbing and Walking Robots (CLAWAR99), Portsmouth, UK.*

Smith, R. (2003). The open dynamics engine user guide. http://opende.sourceforge.net/.

Vaughan, E. (2003). Evolution of 3-dimensional bipedal walking with hips and ankles. Msc thesis, Dept. of Informatics, University of Sussex. (http://www.droidlogic.com/sussex/papers.html).

Whitley, D., Rana, S., and Heckendorn, R. (1999). The island model genetic algorithm: On reparability, population size and convergence. *Journal of Computing and Information Technology*, 7:33–47.