Time and Motion Studies: The Dynamics of Cognition, Computation and Humanoid Walking

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Abstract. Why is walking easy for us and difficult for robots? The conceptual framework of traditional Artificial Intelligence, and constraints from the background of industrial robot designers, means that commercial humanoid design has often ignored the role of natural dynamics of a mechanical system, as illustrated in a Passive Dynamic Walker. We show, using a Dynamical Systems approach and Evolutionary Robotics, how power and control can be added to such systems, demonstrating bipeds in simulation with many degrees of freedom that can walk, balance on a moving platform, and run.

Keywords: Cognition, Dynamical Systems, Passive Dynamic Walking, Evolutionary Robotics

1 Introduction

Currently there is widespread interest, in Japan and around the world, in humanoid walking as a demonstration of just how far robotics and Artificial Intelligence (AI) has gone in replicating this basic but important ability of humans. Particularly in recent years the technical advance seems impressive; but then after further consideration, there is some dissatisfaction at the unnaturalness of the gait, the awkwardness and lack of robustness when the terrain gets rougher. How is it that we find walking so easy, whereas it seems so difficult for humanoid robots even when there is an enormous technical effort put into tackling the problem?

We shall argue here that this is, at least partly, a symptom of constraints in the conceptual framework of a major strand of thought in AI; and we shall agree with an analysis by Pratt (2002) suggesting that the background of most industrial designers of robots has constrained the types of designs they are willing to explore. We shall advocate that a more fruitful conceptual framework for AI and robotics lies in the Dynamical Systems approach, and that this focuses the direction of robotics towards exploiting the natural dynamics of limbs and nervous systems in ways comparable to those of animals and humans. This leads to designs that are no longer constrained by the shackles of conventional AI, nor by the constraints of conventional engineering design philosophy.

A glider, when balanced correctly, can fly in a slow descent without sensors, motors or any pilot in control; the aerodynamics of its interactions with the air around it keeps it stable and flying. Likewise a Passive Dynamic Walker, as described below, can walk without sensors, motors or controller, using the natural dynamics of pendulums and the input from potential energy as it walks down a slope. Careful development from the basic glider, by cautiously adding power and elements of control, has given us the aircraft of today. Likewise we advocate a similar route of development, carefully adding power and elements of control to an initial design that relies solely on the dynamics of its limbs.

In the following sections we start with the historical context to the ideas that constrain conventional robotics today. In discussing models of cognition, we shall contrast the computationalist approach with the Dynamical Systems approach that we advocate; Passive Dynamic Walkers will be treated as a paradigmatic example of this latter approach. One design methodology for designing robots in this fashion is Evolutionary Robotics, so we shall briefly survey how this is done.

Finally we shall give some examples from our recent work using these techniques to develop in simulation powered walking bipeds that have many degrees of freedom, that are robust to major changes in their construction, with graceful degradation of performance even with up to 50% errors in their dimensions. Some of these examples can balance on moving platforms, or react to external pressures to walk forwards or backwards adjusting their speed, relying solely on the natural dynamics of their limbs and their nervous system. Other examples can run. We shall only summarise these achievements briefly here; technical details are given in further papers, available online together with videos. But first we start with a look at the historical roots.

2 Historical Roots

For many centuries, people have made puppets, automata, more recently robots, to demonstrate their technical skills and to amuse, amaze and educate. These have reflected the technology of their day, and illustrated the current conceptions of the human condition. Developments were largely parallel in the West and in Japan, with perhaps one noticeable difference in popular attitudes. In the West, science fiction and Hollywood films have tended to portray robots as threatening rivals to humans, whereas in Japan, by contrast, they are usually taken as friendly; such as the thoughtful and caring Astroboy. Perhaps it is partly these attitudes as well as technical skills that have helped make Japan the world's leader in the development and production of industrial robots.

2.1 European Automata

Some 2,000 years ago Hero of Alexandria described working models of animals and humans, using hydraulics and pneumatics. From around the 14th Century AD onwards, the development of clocks allowed more sophisticated automata. In the 18th Century, elaborate working puppets were made in the clockmaking regions of Switzerland, by the Jaquet-Droz family and others. In the 1820s clockwork mechanisms were developed in a different direction by Charles Babbage, who designed the Difference Engine to calculate mathematical tables, and then the Analytical Engine as the world's first universal digital computer. In the 20th Century, with people such as Alan Turing and John von Neumann, we saw the foundations laid for computing and Artificial Intelligence: the mechanization of some aspects of human *thought* and *calculation*, separated from the *motion* and *actions* of earlier automata.

2.2 Japanese Karakuri

There are records of water-clocks being used in Japan as early as the 6th Century, but as in Europe the building of sophisticated mechanisms had to wait for further developments in clockwork. Hanzo Yorinao Hosokawa was a Master of making Karakuri mechanical puppets in the 18th Century, and in the following century Tanaka Hisashige established a Hall of Automata in Kyoto. He went on to build Japan's first steam locomotive, and directly contributed to the modern industrialization of Japan.

Walking Karakuri inspired humanoid or biped robots, which were pioneered in Japan, initially at Waseda University in the 1960s and 70s. From 1986 onwards, the goal of building a high-quality humanoid robot was taken up by industrial companies such as Honda, and then several other major Japanese corporations. By this time the mechanical engineering problems appeared to be less important than finding appropriate control methods. Computing power was already immense, and the bottleneck has been that of finding suitable control strategies.

2.3 The Present

Nowadays humanoid robots such as Asimo and Qrio are impressive; but considering the resources that have gone into their development, there are some aspects that are still disappointing. Certainly the progress has not matched progress in computing over recent decades. Of course 'walking comes naturally' to us humans, so we are puzzled that it is so difficult to get robots to walk in the same way as we do. Indeed it is very noticeable, for instance, that humanoid robots typically walk with their knees permanently bent. Why is that?

The argument of this paper is that the style in which these bipeds have been designed has been unnecessarily constrained from at least two directions. Firstly, it has usually been assumed that the specific trajectories of robot limbs in Euclidean space must be pre-planned. Secondly, and largely as a consequence of this first assumption, designers have tended to use stiff actuators and materials, so as to maintain close control on the pre-calculated positions of the parts.

It is these constraints, not shared by natural walking bipeds, such as humans, that have led to unnatural and often inefficient robot gaits. Such assumptions are symptomatic of a much wider problem in the field of Artificial Intelligence, and we shall explore this further here, before returning to the specific example of biped walking.

3 Models of Cognition

Cognition in its broadest sense includes all forms of perception and action of a human, animal, robot or other artificial model of a creature. Traditionally exploiting the latest technology as a model for the mechanisms of the mind, we have moved beyond the clockwork, and then telephone exchange models of a century ago, to the use of the most powerful technology of the last 50 years, computing. Good Old Fashioned AI (GOFAI) does not just use computers as a *tool* to assist in investigations, but usually takes the *computer itself* as some model for the mind. It will be suggested here that this unfortunate assumption is flawed, and has for instance held back the development of walking robots.

3.1 GOFAI

Computers were intended from the start to carry out algorithms or procedures, on symbols or numbers. Babbage's Analytical Engine, and then the Turing Machine, would accept the symbolic statement of a problem as input, and then mechanically follow the provided rules until it terminated with the desired result. Turing got his ideas for the Turing Machine from considering how a human calculator would follow the relevant rules for doing a mathematical calculation such as long division, and then turning the formal method into an abstract mechanism. This then formed the basis for the fast computers that now sit on our desks. A crucially important demonstration by Turing was that the Universal Turing Machine (UTM) could emulate any other conceivable Turing Machine, and hence was in principle as powerful as any of them. Provided that one has the right software and sufficient memory for the job, an Apple can emulate an IBM PC and *vice versa* (strictly speaking a UTM needs limitless memory to handle tasks of arbitrary complexity, but for practical purposes one just needs enough for the task to hand). This leads to the attractive idea that once one has sufficient hardware it is in some sense unimportant which particular brand or design one has, thereafter there are only software issues to worry about. What if the human brain was just another brand of UTM, no more and no less powerful in principle as any other? This is the dream — or fantasy — of cognitivism and GOFAI; if true, it would of course make sense to consider cognition to be a form of computation, and also make sense to enquire what operating system, what programming language is used in the brain.

Since computers require problems to be presented, and solved, in formal symbolic fashion, the GOFAI scientist who takes computers as the model for cognition will assume that *all* aspects of cognition, in a human or a robot, should be considered as an exercise in abstract problem-solving. So the business of finding ones way around a room should first, if one follows GOFAI principles, be turned into some abstract formal representation of the environment and the robot's position within it, and of the possible degrees of freedom that are available. Using an "internal representation" of the problem, in Euclidean coordinates or the equivalent, possible trajectories can be planned and calculated before being put into action. This is what Brooks (1995) has called the SMPA or Sense, Model, Plan, Action approach.

3.2 The Dynamics of Computation and GOFAI

In a world where there is perfect knowledge, with no surprises, no noise, then in principle all the future trajectories of a robot could be calculated in advance and at leisure. Some industrial automation processes do come near to this ideal, but for mobile robotics the real world is very different. So to take account of any surprises, a constant succession of "snapshots" of the environment need to be taken with the relevant robot sensors, and the world model, and hence plan, needs to be recalculated each time.

In the cinema, the latency of human vision allows 25 or 30 frames a second to appear to us as continuous. But the GOFAI snapshot approach, arising from the dynamics of the process of computation, comes with some price to pay. Firstly, of course, the computer must be fast enough to do all the necessary calculations within each short interval; this becomes less of a problem as clock rates of processors improve. But secondly, there is an inevitable tendency to analyse even a dynamical process such as biped walking as a succession of steps between instantaneous positions; the dynamic has been reduced to transitions between static snapshots. One consequence is the rather unnatural underlying principles to the walking style of many commercial biped robots today.

3.3 The Dynamical Systems approach to Cognition

There is a contrasting approach to GOFAI, which can be loosely termed the Dynamical Systems (DS) approach. Here we give a version of a DS approach to human or animal cognition, before considering how this could translate to robots.

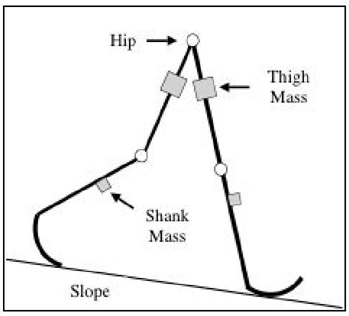
The nervous system of an animal is an organized system of physical components such as neurons, their connecting axons and dendrites, and their substrate, with electrical and chemical activity swirling around. The picture that neuroscientists give us is still changing; it is only in the last decade or so that the significance of chemical transmission as well as electrical transmission between neurons has been noted as significant. But the universal working assumption is that in principle there is a finite (though extremely large) number of physical variables that could be picked out as relevant to the workings of the machinery of the brain; and these variables continuously interact with each other according to the laws of physics and chemistry.

Suppose we have a finite number of variables and we can in principle write down an equation for each one, that states how its rate of change at any instant can be given by a formula related to the instantaneous values of itself and some or all of the other variables; then formally speaking we have a Dynamical System. In the case of a nervous system, the variables are not only internal ones, but also include sensory inputs and motor outputs, the interactions with the world around it.

A GOFAI person may well find all this acceptable, so far. But here comes the difference, particularly so far as this has implications for building robots: rather than treating the set of equations that form a DS as equations to be *solved in real time* through computational methods as in the SMPA approach, we treat the design problem as that of finding the right set of components, and appropriate parameter values, so that the robot dynamics just "naturally does the right thing!" An example is needed to make this clear.

3.4 Passive Dynamic Walking

McGeer (1990) designed and simulated a two-dimensional bipedal passive dynamic walker (PDW) with knee joints and curved feet. This has just 4 component parts, and 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, no sensors and no control system (Figure 1a). The natural dynamics of a pendulum keep the walking motion going, and when the parameters are in the right region it is resistant to small perturbations. 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.



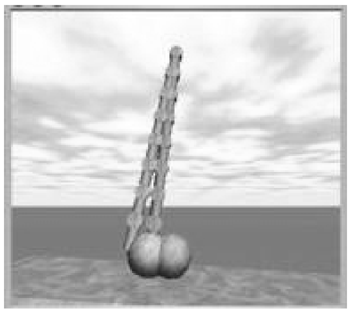


Figure 1. (a) Components of a basic Passive Dynamic Walker. (b) 7-knee version.

The simulations are within a computer, and typically the design process also requires computations. But the final product, when walking down a slope, has no internal computational process, and unlike the GOFAI approach it merely exploits the natural dynamics of coupled pendulums.

This relatively simple PDW is the paradigmatic example of a DS approach to designing a robot; but it need not be restricted to simple designs. In Figure 1b is a 7-kneed PDW, that can walk downhill a few steps, developed in simulation by Vaughan (2003). Quicktime movies of this and the other examples discussed below are available online at *www.droidlogic.com*.

3.5 The Role of Computation in a Dynamical Systems Approach

This simple PDW clarifies the distinction between GOFAI and DS approaches. The physically built version, such as by Collins (Collins et al., 2001), is just 4 mechanical components with joints, and there is clearly no onboard computation of any kind. Quite possibly computers and computations may have played a role, perhaps an important role, in the design of the components, in the choice of parameter values, perhaps initial testing in a simulation, a computational physics engine; but that does not make the PDW itself a computational device.

When one starts to make these bipeds more complex, as we shall see below, then components of an artificial nervous system may be added; components that may have dynamics on a faster timescale than those of pendulum limbs, an analogue of the dynamics of neurons in a mammalian nervous system. Perhaps springs and cogs and ratchets, perhaps transistors and capacitors and resistors in an analogue electrical circuit — the faster dynamics of these still do not make it a computational device.

At this stage it should be made absolutely clear that by computational device we mean something equivalent to a UTM, provided, if not with infinite memory, then with sufficient memory to handle the job to hand. This, after all, is precisely what GOFAI people were referring to when they laid the foundations for their approach. We are using ‘computational’ in this technical sense, not in the ill-defined everyday sense where any complex electronic device may be advertised as a computer.

To add a further layer of subtlety to this point: quite often people taking the DS approach to robotics may use a computer and its internal timing device to emulate the dynamics of such fast nervous system components. Our desktop computers actually go beyond the capacity of a UTM in typically providing an onboard clock, something the Turing Machine does without; and it is this that makes possible real-time emulation of such dynamics. If and when we do this, it is for reasons of practical convenience and does not *ipso facto* turn the artificial nervous system into a computational device, in the GOFAI sense. After all, we can tell the time with a sundial, or a mechanical clock with a pendulum, or a digital wristwatch, and the fact that we can use the last method does not suddenly turn ‘telling the time’ into a computational task.

There is a very real and important difference between the GOFAI and the DS approach to cognition and robotics; this is reflected in the design process.

4 Designing Robots with a Dynamical Systems Approach

In contrast to the GOFAI approach of providing the robot with a comprehensive model of the external world in symbolic form, the DS approach is one of “getting the dynamics of interaction right.” Often this can be done in the first instance within a simulation, using tools such as the physics engine ODE (Smith 2003). Simple systems with few degrees of freedom may be designed through analysis of the requirements, but for more complex systems we need some automatic design process such as through learning or through artificial evolution.

Moving beyond the simple PDW that has no control parts other than the limbs themselves, if we want to add power, and further control for the robot to adjust adaptively to different surfaces and to disturbances, then we need to add the robot equivalent of a nervous system or brain. But this need not behave like a computer, indeed we want this to be a DS in its own right, interacting in real time through motors and sensors with the environment.

For reasons of practicality, in many experiments we use Artificial Neural Networks (ANNs) as simulated in real time with the aid of a computer. In particular one favorite class of ANNs is the CTRNN, Continuous Time Recurrent Neural Network (Beer 1995). This is a potentially fully-connected network of real time leaky integrators with specified temporal constants, and is an archetypal dynamical system. The class of CTRNNs has the useful property of universal approximation to any smooth dynamical system (Funahashi and Nakamura 1993); in other words, given any DS where the variables change smoothly, we can in principle find a CTRNN, with enough nodes, that will approximate its dynamical behavior to any desired degree of accuracy.

One approach to the design of such systems is to follow the course of evolution fairly literally; this gives us the relatively new field of Evolutionary Robotics (ER), as a methodology for designing artificial creatures using artificial Darwinian evolution.

4.1 Evolutionary Robotics

Suppose that we wish to design a biped robot that will walk efficiently and robustly over a particular type of surface. Then as Evolutionary Roboticists (Harvey et al. 1996) we set up a test environment, where robots can be evaluated and scored on their fitness at this task. We then work with a population of robots that have various designs of limbs and nervous system architecture; or more practically, we usually work with one robot and a population of possible architectures. The components of the nervous system are real or idealized physical components such as the nodes and links of a CTRNN. In our role as the Creators of this artificial world, we specify some appropriate mapping between genotypes, strings of artificial DNA that may well be simply composed of 0s and 1s, and phenotypes by which we mean the actual way in which the limbs and nervous system is assembled from the available components.

At the simplest level, the genotype may be (when translated) in effect a blueprint for assembling the robot with its nervous system. With more sophisticated mappings, it may act more like a recipe 'for baking a cake', directing and influencing (perhaps in league with environmental influences) the final architecture without actually explicitly specifying its form. Whichever form of mapping we choose to use, the result should be that the search through the space of possible architectures is paralleled by an equivalent search through the space of possible genotypes, of artificial DNA. Indeed, since these genotypes allow inheritance of genetic material from robot parents selected for their fitness at a task, and mutations to the genotype – a few random changes to the 0s and 1s – allow for variation, we have all the necessary ingredients for Darwinian evolution: Heredity, Variation and Selection.

4.2 The Evolutionary Procedure

Artificial evolution typically consists of repeated rounds, or generations, of testing a population of candidate designs, and selecting preferentially the fitter ones to be parents of the next generation. The next generation consists of offspring that inherit the genetic material from their selected parents; much the same as farmers have been doing for thousands of years in improving their crops and their livestock. The initial population is based on completely random genotypes of artificial DNA, so the only direction given to the evolutionary design process is the indirect pressure of selection. The genotypes in following generations are usually mixed through sexual recombination, and further varied through mutations, so as to introduce further variety for selection to choose from.

As far as possible this is an automated, hands-off process. The human designer's input is limited to specifying the mapping from genotype to phenotype, and choosing the selection process that allocates fitness scores to each robot. This depends on the cognitive ability that is desired, and usually requires careful thought. To give a simple example, if one wishes to craft a fitness function intended to promote the movement of a robot across a crowded floor without bumping into anything, then one might be tempted to judge the fitness by how far the robot travels in a fixed time. Although high scores will be achieved through evolution, the result may well be disappointing as typically such scores will be gained by rapid rotation around a tight circle; it turns out to be necessary to craft the fitness function so as to give more credit for (fairly) straight movement and less for tight turns.

Although the human designer has set up the scenario intended to select, over many generations, for the desired behavior, it is important to note two things. Firstly, no individual robot is given any feedback as to how well its behavior is accumulating fitness – so later generations only succeed if it is in their inherited 'genetic nature' to behave appropriately. Secondly, more often than not the finally evolved robot nervous system is complex and opaque, it is difficult and maybe impossible to analyze just how the job is done.

5 Humanoid Walking

Most walking robots that have been built use the GOFAI assumption that the specific trajectories of robot limbs in Euclidean space must be pre-planned. Largely as a consequence of this first, designers have tended to use stiff actuators and materials, so as to maintain close control on the pre-calculated positions of the parts.

Pratt (2002) gives an interesting and thoughtful analysis of this:-

"Experiments … … have led us to believe that a significant handicap of current

> biomimetic robots is their typically high impedance actuators and control systems. The impedance we refer to is a measure of how unplanned variations to position, movement, or acceleration caused by the outside world are resisted (*i.e.,* impeded) by a joint or set of joints intent on following a specific trajectory. … …
> The Honda robot, for example, uses a mode of control ([ZMP] Zero-Moment Point Control (Vukobratovic and Juricic, 1969)) that requires the robot to accurately obey precisely calculated trajectories, modified only by a few force sensors in the ankles (Hirai *et al.*, 1998). This is a high impedance solution."

If the leg of a biped is allowed to straighten up at the knee, then the calculations required by ZMP have a singularity with no sensible solution. The basic explanation of the unnatural bent-knee gait that is used by Asimo is that it avoids this problem.

However natural systems, animals and humans, have relatively low impedances, particularly when compared to position-controlled robots. Pratt (2002) points out that most industrial designers of robots have a background biased towards high impedance mechanisms and control; also that engineers have found it typically much easier to measure positions rather than forces.

The simple PDW is an extreme example of a minimally stiff biped that exploits natural dynamics, but is restricted to walking downhill under gravity and is not very robust to perturbations. One sensible route to take in order to develop a powered and more adaptive biped is to start with a PDW and add as little power and further control as one can get away with.

5.1 Gliders and Walkers

A fruitful analogy used within our group (Vaughan 2003, Vaughan et al., 2004a, 2004b) is that of the role of gliders in the development of human flight. The origins of aviation with the early pioneers, including particularly the Wright brothers, lay in initially studying and analyzing un-powered flight with minimal controls, i.e. gliding. If we can design a suitably stable glider, initially for simple uncontrolled flight with no more power than that provided by potential energy, then we are in a much stronger position when we start to be more ambitious and try to add some form of steering. Similarly when we try to add power, to allow steady flight or even ascent as well as descent, then we can have some confidence that we are starting in a promising region of design space if we know that reducing the power to a minimum will allow stable flight.

The analogy carries almost directly over to PDWs. Let us optimize, through any technique including ER, a fully passive dynamic walker that can 'glide' down a slope under potential energy alone; then let us use this design as a starting point, to have control and power added and to be modified as necessary to cope with these changes.

5.2 Earlier example of PDW with Power

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; "Series elastic actuators" allowed forces, rather than positions, to be specified. 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. However 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.

5.3 Our Powered PDW Project

At Sussex we are likewise adding power and further control to a PDW, but with a stronger emphasis on automating the design of the control system through evolutionary and other learning techniques. In this paper we shall only give a brief summary of achievements to date, and refer people to previously published papers (Vaughan 2003, Vaughan et al., 2004a, 2004b) and website on *www.droidlogic.com* for more technical details.

A preliminary stage beyond the basic PDW has been the development, within simulation using ODE (Smith 2003), of a 10 degree of freedom bipedal robot that can walk down a slope with no sensors or actuators. The extra degrees of freedom include 2 axes of rotation at each ankle, moderated by springs. The evolutionary design process determines appropriate values for the limb proportions, the spring parameters, and the centre of mass of each limb component, as indicated in Figure 2a. The fact that there are no sensors or actuators implies that control systems are only needed to inject power and stabilise these dynamic machines. Controlling all the trajectories as in ZMP is unnecessary, computationally expensive and inefficient.

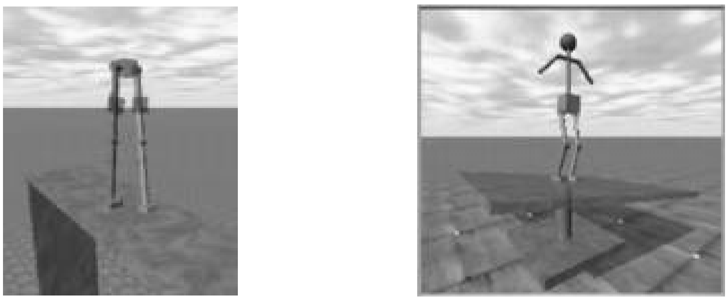


Figure 2. (a) 10 degree of freedom PDW. (b) Balancing on a moving platform.

The same machine can be powered on a flat surface without complex foot sensors (complex foot sensors are absolutely required for ZMP machines). 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.

More complex controllers can also scale up. We have designed in simulation a 6 degree of freedom biped with a torso that when pushed walks either forward or backwards just enough to release the pressure placed on it. Just as a tango dancer uses a dance frame to control the movements of their follower, external forces are a subtle way to control the machines speed. When the machine is subjected to noise in its body's size, weight, or actuators as well as external forces it demonstrates the ability to dynamically adapt its gait through feedback loops between its actuators and sensors. With 10% errors in the dimensions the performance is only slightly degraded, and even with a 50% error rate there was still residual capacity to walk a number of steps.

Experiments with the design of these bipeds show that they can be adapted to carry weights efficiently. In studies conducted in Kenya, women there were observed to carry great weights on their heads while using very little energy (Eugenie 2001). This was attributed to the observation that they walk like inverted pendulums supporting the weight on a straight leg as they move forward. Since our bipeds similarly walk on a straight leg, unlike those using ZMP, they have the capacity for similar efficiency. Taking the original design through 200 further generations of evolution, selecting for improved efficiency, it was possible to adapt the design so as to be able to carry an extra load of 200% of its body weight at a cost of just 51% extra energy.

A 10 degree of freedom biped with a torso has been designed with sensors and an evolved Artificial Neural Network that can balance on a moving platform even under extreme conditions; see Figure 2b.

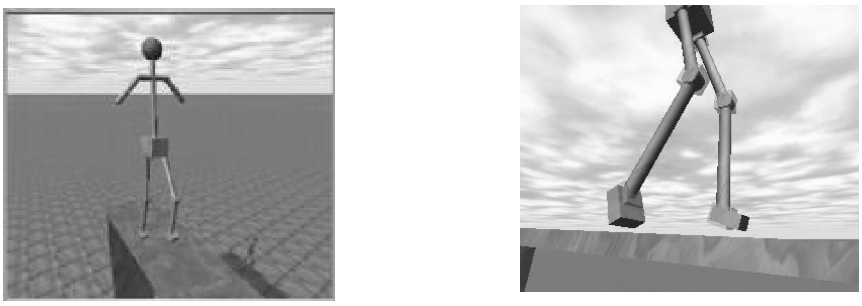


Figure 3. (a) Running. (b) Both feet leave the ground.

Finally, we have now extended these techniques to design within simulation a biped with torso that can run, Figure 3a. Quicktime movies are available on the website, and from Figure 3b it can be seen that indeed both feet do leave the ground.

5.4 Future Directions

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. There have been many cases where systems designed to work within simulations have failed to transfer into a physical realisation, often because the simulation omitted some physical factors that might have appeared of minor importance, but whose influence turns out to be crucial. In particular, a brittle design that relies on precise values of parameters will often fail to transfer to the real world.

These problems have been faced within ER for some time, and some strategies have been developed to get past this problem (Harvey et al., 1996; Jakobi 1997, 1998a, 1998b). The strategy of putting significant amounts of the right kinds of noise into a simulation used for ER and steering the evolutionary design of control systems towards those that are robust to even extreme noise, has been demonstrated to be capable of generating controllers in simulation that then do indeed function on a physical robot. This has been the motivation for some of the examples given above where the designs are shown to be robust in simulation to significant changes in the dimensions and parameters.

6 Conclusion

The style of robotics advocated here has significant differences from that driven by GOFAI assumptions and the common industrial bias towards high impedance mechanisms. A main purpose of this paper has been to explore just where these assumptions come from, and what effects they have on robot design.

The Passive Dynamic Walker is the archetypal example of a walking biped that can only be understood in Dynamical Systems terms. We have shown, following the glider analogy, how this can be taken as a starting point for adding control and power through ER techniques.

If we want to persuade people, perhaps against all their instincts, to take up an unfamiliar way of tackling this problem of humanoid walking, then the ultimate test is to demonstrate that it achieves results. The walking, running and balancing bipeds shown here, evolved in physical simulations with significant amounts of noise, should be compared with the current state of the art using other methodologies. We believe that this approach offers the best prospects for the future.

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