

Evolving Humanoids: Using Artificial Evolution as an Aid in the Design of Humanoid Robots

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1. Introduction

This chapter presents a survey of the state of the art in evolutionary humanoid robotics, focusing mainly, but not exclusively on the use of evolutionary techniques for the design of a variety of interesting behaviours in humanoid robots; both simulated and embodied.

It will discuss briefly the increasing importance of setting robot standards and of benchmarking mobile and service robot performances, especially in the case of future humanoid robots, which will be expected to operate safely in environments of increasing complexity and unpredictability.

We will then describe a series of experiments conducted by the author and his colleagues in the University of Limerick involving the evolution of bipedal locomotion for both a simulated QRIO-like robot, and for the Robotis Bioloid humanoid robot. The latter experiments were conducted using a simulated version of this robot using an accurate physics simulator, and work is ongoing in the transfer of the evolved behaviours to the real robot. Experiments have been conducted using a variety of different environmental conditions, including reduced friction and altered gravity.

The chapter will conclude with a look at what the future may hold for the development of this new and potentially critically important research area.

2. Evolutionary humanoid robotics

Evolutionary humanoid robotics is a branch of evolutionary robotics dealing with the application of evolutionary principles to the design of humanoid robots (Eaton M, 2007). Evolutionary techniques have been applied to the design of both robot body and 'brain' for a variety of different wheeled and legged robots, e.g. (Sims, 1994; Floreano and Urzelai, 2000; Harvey, 2001; Pollack et al., 2001; Full, 2001; Zykov et al., 2004; Lipson et al., 2006; Bongard et al., 2006). For a good introduction to the general field of evolutionary robotics see the book by Nolfi and Floreano (Nolfi and Floreano, 2000).

In this chapter we are primarily concerned with the application of evolutionary techniques to autonomous robots whose morphology and/or control/sensory apparatus is broadly human-like. A brief introduction to the current state of the art with regard to humanoid robotics including the HRP-3, KHR-1 and KHR-2, Sony QRIO and Honda ASIMO and P2 is contained in (Akachi et al., 2005). Also see the articles by Brooks (Brooks et al., 1998; Brooks, 2002) and Xie (Xie et al., 2004) for useful introductory articles to this field.

There are several possible motivations for the creation of humanoid robots. If the robot has a human-like form people may find it more easy and natural to deal with than dealing with a purely mechanical structure. However as the robot becomes more human-like, after a certain point it is postulated that small further increases in similarity result in an unnerving effect (the so called "uncanny valley" introduced by Mori (Mori, 1970) and elaborated by MacDorman (MacDorman, 2005)). The effect is seen to be more pronounced in moving robots than in stationary ones, and is thought to be correlated to an innate human fear of mortality. Another reason, suggested by Brooks (Brooks, 1997) and elaborated recently by Pfeifer and Bongard (Pfeifer and Bongard, 2007) is that the morphology of human bodies may well be critical to the way we think and use our intellect, so if we wish to build robots with human-like intelligence the shape of the robot must also be human-like.

Ambrose argues that another reason for building robots of broadly humanoid form is that the evolved dimensions of the human form may be (semi-) optimal for the dexterous manipulation of objects and for other complex motions; he however argues that the human form should not be blindly copied without functional motivation (Ambrose and Ambrose, 2004).

A final, and very practical reason for the creation of future humanoid robots is that they will be able to operate in precisely the environments that humans operate in today, This will allow them to function in a whole range of situations in which a non-humanoid robot would be quite powerless, with all of the inherent advantages that this entails. Brooks discusses this issue further in his later paper on the subject (Brooks et al., 2004).

The hope is that by using artificial evolution robots may be evolved which are stable and robust, and which would be difficult to design by conventional techniques alone. However we should bear in mind the caveat put forward by Mataric and Cliff (Mataric and Cliff, 1996) that it is important that the effort expended in designing and configuring the evolutionary algorithm should be considerably less than that required to do a manual design for the exercise to be worthwhile.

We now review briefly some of the work already done, and ongoing, in the emerging field of evolutionary humanoid robotics; this list is not exhaustive, however it gives a picture of the current state of the art.

In an early piece of work in this area Bongard and Paul used a genetic algorithm to evolve the weights for a recurrent neural network with 60 weights in order to produce bipedal locomotion in a simulated 6-DOF lower-body humanoid using a physics-based simulation package produced by MathEngine PLC. (Bongard and Paul, 2001) Inputs to the neural network were two touch sensors in the feet and six proprioceptive sensors associated with each of the six joints. Interestingly, in part of this work they also used the genome to encode three extra morphological parameters - the radii of the lower and of the upper legs, and of the waist, however they conclude that the arbitrary inclusion of morphological parameters is not always beneficial.

Reil and Husbands evolved bipedal locomotion in a 6-DOF simulated lower-body humanoid model also using the MathEngine simulator. They used a genetic algorithm to evolve the weights, time constants and biases for recurrent neural networks. This is one of the earliest works to evolve biped locomotion in a three-dimensional physically simulated robot without external or proprioceptive input. (Reil and Husbands, 2002)

Sellers et al. (Sellers et al. 2003; Sellers et al. 2004) have used evolutionary algorithms to investigate the mechanical requirements for efficient bipedal locomotion. Their work uses a simulated 6-DOF model of the lower body implemented using the Dynamechs library. The

evolutionary algorithm is used to generate the values used in a finite-state control system for the simulated robot. They suggest the use of an incremental evolutionary approach as a basis for more complex models. They have also used their simulations to predict the locomotion of early human ancestors.

Miyashita et al. (Miyashita et al., 2003) used genetic programming (GP) to evolve the parameter values for eight neural oscillators working as a Central Pattern Generator (CPG) interacting with the body dynamics of a 12 segment humanoid model, in order to evolve biped walking. This work is in simulation only, and a maximum of ten steps of walking were evolved, because of the instability of the limit cycles generated.

Ishiguro et al (Ishiguro et al.,2003) used a two stage evolutionary approach to generate the structure of a CPG circuit for bipedal locomotion on both flat and inclined terrain. They used MathEngine to simulate the lower body of a 7-DOF humanoid robot. An interesting aspect of this work is the adaptability of the evolved controllers to gradient changes not previously experience in the evolutionary process.

Zhang and Vadakkepat have used an evolutionary algorithm in the generation of walking gaits and allowing a 12-DOF biped robot to climb stairs. The algorithm does, however, contain a degree of domain-specific information. The robot is simulated using the Yobotics simulator and the authors claim the performance has been validated by implementation on the RoboSapien robot (Zhang and Vadakkepat, 2003)

Unusually for the experiments described here, Wolff and Nordin have applied evolutionary algorithms to evolve locomotion directly on a real humanoid robot. Their approach is that starting from a population of 30 manually seeded individuals evolution is allowed to proceed on the real robot. Four individuals were randomly selected then per generation and evaluated, the two with higher fitness then reproduce and replace the individuals with lower fitness. Nine generations were evaluated, with breaks between each generation in order to let the actuators rest. The physical robot used was the ELVINA humanoid with 14-DOF; 12 of these were subject to evolution. While the evolutionary strategy produced an improvement on the hand-developed gaits the authors note the difficulties involved in embodied evolution, with frequent maintenance of the robot required, and the regular replacement of motor servos. (Wolff and Nordin, 2002). Following this the authors moved to evolution in simulation using Linear GP to evolve walking on a model of the ELVINA robot created using the Open Dynamics Engine (ODE) (Wolff and Nordin, 2003).

Endo et al. used a genetic algorithm to evolve walking patterns for up to ten joints of a simulated humanoid robot. Work was also done on the co-evolution of aspects of the morphology of the robot. The walking patterns evolved were applied to the humanoid robot PINO. While stable walking gaits evolved these walking patterns did not generally resemble those used by humans (Endo et al., 2002; Endo et. al 2003). They note that an interesting subject for study would be to investigate what constraints would give rise to human-like walking patterns. A characteristic of our own current work is the human-like quality of the walks generated, as commented on by several observers.

Boeing et al. (Boeing et. al, 2004) used a genetic algorithm to evolve bipedal locomotion in a 10-DOF robot simulated using the Dynamechs library. They used an approach that has some parallels with our work; once a walk evolved this was transferred to the 10-DOF humanoid robot 'Andy'. However few of the transferred walks resulted in satisfactory forward motion illustrating the difficulties inherent in crossing the 'reality gap'.

Finally, Hitoshi Iba and his colleagues at the University of Tokyo have conducted some interesting experiments in motion generation experiments using Interactive Evolutionary Computation (IEC) to generate initial populations of robots, and then using a conventional GA to optimise and stabilise the final motions. They applied this technique to optimising sitting motions and kicking motions. IEC was also applied to a dance motions which were implemented on the HOAP-1 robot; the kicking motions were confirmed using the OpenHRP dynamics simulator (Yanese and Iba, 2006). They have also demonstrated the evolution of handstand and limbo dance behavioural tasks (Ayedemir and Iba, 2006). The next section introduces our own work in evolving bipedal locomotion and other behaviours in a high degree-of-freedom humanoid robot.

3. Evolving different behaviours in simulation in a high-DOF humanoid

Bipedal locomotion is a difficult task, which, in the past, was thought to separate us from the higher primates. In the experiments outlined here we use a genetic algorithm to choose the joint values for a simulated humanoid robot with a total of 20 degrees of freedom (elbows, ankles, knees, etc.) for specific time intervals (keyframes) together with maximum joint ranges in order to evolve bipedal locomotion. An existing interpolation function fills in the values between keyframes; once a cycle of 4 keyframes is completed it repeats until the end of the run, or until the robot falls over. The humanoid robot is simulated using the Webots mobile robot simulation package and is broadly modelled on the Sony QRIO humanoid robot (Michel, 2004; Mojon, 2003). (See (Craighead et. al., 2007) for a survey of currently available commercial and open-source robot simulators). In order to get the robot to walk a simple function based on the product of the length of time the robot remains standing by the total distance travelled by the robot was devised. This was later modified to reward walking in a forward (rather than backward) direction and to promote walking in a more upright position, by taking the robots final height into account. The genome uses 4 bits to determine the position of the 20 motors for each of 4 keyframes; 80 strings are used per generation. 8 bits define the fraction of the maximum movement range allowed. The maximum range allowed for a particular genome is the value specified in the field corresponding to each motor divided by the number of bits set in this 8 bit field, plus 1. The genetic algorithm uses roulette wheel selection with elitism; the top string being guaranteed safe passage to the next generation, together with standard crossover and mutation. Two-point crossover is applied with a probability of 0.5 and the probability of a bit being mutated is 0.04. These values were arrived at after some experimentation.

Good walks in the forward direction generally developed by around generation 120. The evolved robots have developed different varieties of walking behaviours (limping, side-stepping, arms swinging, walking with straight/flexed knees etc.) and many observers commented on the lifelike nature of some of the walks developed. We are also exploring the evolution of humanoid robots that can cope with different environmental conditions and different physical constraints. These include reduced ground friction ('skating' on ice) and modified gravitation (moon walking). Fig.1 shows an example of a simulation where a walk evolved in a robot with its right leg restrained, and Fig.2 shows an example of an evolved jump from a reduced gravity run. Further details of these experiments are given in (Eaton and Davitt, 2006; Eaton and Davitt, 2007; Eaton, 2007).

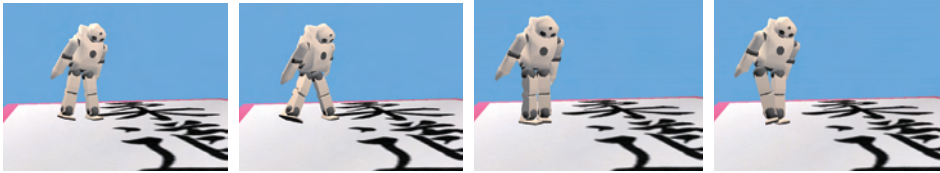


Figure 1. QRIO-like robot walking with right leg restrained



Figure 2. An example of an evolved jump from a reduced gravity run

4. The importance of benchmarking

An important task currently facing researchers in the field of advanced autonomous robots is the provision of common benchmarks for performance evaluation. Current benchmarks, while useful, have their problems. A current de facto standard in this field is the RoboCup annual challenge. RoboCup operates in four categories: simulated teams, a small size league, a middle size league, and legged robots. An example small size robot is Khepera; a typical middle sized robot is the Pioneer platform, and the Sony artificial dog fits in the third category. There is also a humanoid league which of course is of specific interest. Individual skills to be mastered include navigation and localisation on the field of play, and the selection of optimal paths. Inter-individual skills include the coordination of movements with playing partners in order to pass accurately. At the top level the tasks of strategy generation and recognition of opponents' strategies are crucial.

Criticisms of RoboCup stem from the controlled environment in which the robots operate, and the fact that soccer-playing skills are quite specific and may lead to the development of highly focused robots of little use for any other task. Also, the self-localisation problem is considerably simplified by the use of highly artificial landmarks.

We recommend, therefore, the provision of a set of specifically designed experimental frameworks, and involving tasks of increasing complexity, rigorously defined to facilitate experimental reproducibility and verification. Steps are being taken in this direction, for example the European Union RoSta (Robot Standards) initiative, however we recommend the acceleration of these efforts for the provision of a universally acceptable set of benchmarks that can be used by robotics developers. By allowing easier comparisons of results from different laboratories worldwide this will facilitate important new developments in the field of intelligent autonomous robots, and humanoid robots in particular. For a further discussions of this important topic see (Gat,1995) and (Eaton et al, 2001).

5. The Bioloid robotic platform

To implement our simulated robots in the real world we currently use the Bioloid robot platform which is produced by Robotis Inc., Korea. This platform consists of a CPU, a number of senso-motoric actuators, and a large number of universal frame construction pieces.

Using this platform it is possible to construct a wide variety of robots, from simple wheeled robots to complex humanoid robots with many degrees of freedom. In addition, because of the ability to construct a range of robots with slightly different morphologies it lends itself well to evolutionary robotics experiments in which both robot "body and brain" are evolved. We initially constructed a "puppy-bot" with this kit (Fig. 3) which can walk, avoid obstacles and perform several cute tricks. With this experience we then constructed the Bioloid humanoid robot which has 18 degrees of freedom in total. A modified version of this humanoid robot was used for Humanoid Team Humboldt in the RoboCup competitions in Bremen 2006. (Hild et. al 2006) Two pieces of software are provided with the Bioloid system; the behaviour control programmer, and the motion editor (Fig.4) The behaviour control programmer programs the humanoids response to different environmental stimuli, while the motion editor describes individual motions based on the keyframe concept.

It is interesting to note the different reactions of people to the "puppy-bot" and the humanoid robot respectively. Both have quite an impressive repertoire of built in behaviours and motions, which we were able to add to. The puppy-bot can stand up, walk on four legs, avoid obstacles and, in a real attention-grabber, stand on its head (the "ears" providing suitable support) and wave its feet in the air. The humanoid on the other hand can clap its hands in response to a human clapping, walk (badly), do a little dance, get up from lying down, and avoid obstacles of a certain height.

Both repertoires are impressive on paper, but one would, perhaps, imagine the humanoid robot to elicit more amazement, it being more complex (18DOF as opposed to 15DOF) and the fact that it is in the general shape of a human. The opposite turns out to be the case. The humanoid certainly impresses, as shown by intense silence punctuated by surprised gasps. However the puppy-bot has the ability to consistently evoke a reaction of unbridled amazement and glee with its antics. Part of the answer, perhaps, comes from the level of expectation. We do not expect much of a puppy except to waddle around and act cute. And the puppy-bot does this in spades. Human behaviour, however, generally tends to be considerably more sophisticated. So when a humanoid robot walks, we do not consider what a difficult task this was to program (or perhaps evolve), but how inefficient it appears compared to human walking. And so on with other behaviours and abilities. Perhaps another factor is the popular media portraying CGI robots doing amazing tricks, beside which our real robots cannot compete (yet). And perhaps the third issue is a certain element of latent fear. The robot looks (marginally) like us, can locomote somewhat like us - in 10 years time will it be looking to take over our jobs?



Figure 3. The puppy-bot (left) and Bioloid humanoid robot (right)

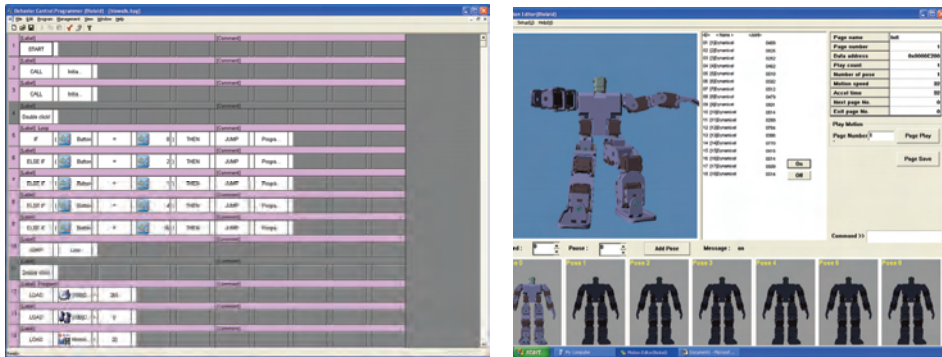


Figure 4. On the right the Bioloid Motion Editor with 18-DOF Bioloid humanoid. The current pose is shown in the main box, the pose sequence (up to six poses) is shown in the lower boxes, the Behaviour Control Programmer is shown on the left

6. The creeping mechanisation of society - a philosophical aside

As AI researchers strive, on one hand, to recreate human-like intelligence in machine form on the other hand people are being coerced and cajoled into acting and thinking in an increasingly mechanised fashion. While machines may indeed one day achieve human-level intelligence (or beyond), however we define this, the opposite will never be the case. Indeed the gap can only get wider as machinery and its computing ability becomes ever more sophisticated. There are those who argue that there is no real need for concern. By removing the drudgery from many everyday tasks (travelling to work, washing clothes etc.) are these machines, in one sense, not acting in exactly the opposite fashion. In any case, they may argue (jokingly or not) that perhaps we are seeing the nascent genesis of a new breed of intelligence; "*Human mark 2.0*" as our natural descendants, as evidenced by the recent rapid advances in the field of humanoid robotics, and indeed in evolutionary humanoid robotics as we discuss in this article.

And here lies the nexus of the problem as I see it. The potential damage may not be so much material (ever increasing workloads, tighter schedules, living and working in box-like conditions, communications becoming ever more distant and impersonal, etc.) as psychological. In the 'battle' between humans achieving machine-like standards of dexterity and speed, and machines achieving human-like intelligence there can only be one winner. Why do so many people nowadays turn increasingly to escape from the pressures of "everyday" life (which only 150 years ago would have been far from "everyday") to alcohol and other drugs? What is the reason for the recent upsurge in depression and associated ills in men, especially young men in the advanced societies? For example, in Japan, arguably the most advanced technological nation on the planet, increasing numbers of young men are turning "*hikikomori*" (literally "pulling away"), where a significant proportion (by some estimates up to 1% of the entire Japanese population) are withdrawing completely from society and locking themselves away in their room for several months, and even years at a time.

Perhaps deep down they feel, or have an inkling of, an ongoing battle in which they have no control, in which there can be only one winner, and in which they think they will feel ever more redundant. At least human females (of child-bearing age) can currently perform one

task which is impossible for machines: that is to produce the next generation of humanity; for men their spheres of dominance over machines in so many areas is being gradually whittled away with no end in sight. Like the native Americans or the Aboriginal races in Australia, when faced with what seems an impossible future- many simply give up.

Fear is insidious. Fear is pervasive. And the most insidious and pervasive fear of all is fear of the unknown, or in this case fear from an unrecognised source. It is now time for us to address these issues squarely. Rather than blindly embracing future technologies for technologies' sake we should be more critical as to their potential future benefits and drawbacks for humanity as a whole. There may well be significant social implications but the consequences of inaction could well have far reaching consequences for us all.

7. Evolving bipedal locomotion in a real humanoid robot

Returning to the main theme of this chapter, we have now constructed an accurate model in Webots of the Bioloid humanoid robot (Fig.3, right) in order to test our techniques in the real world. As in the case for the simulated experiments we use a genetic algorithm to evolve the positions of the joints of the robot at four points in the walk cycle. An existing interpolation function fills in the joint values between these keyframes and the cycle repeats until the robot falls over or until a set time limit is reached. The fitness function used is again a function based mainly on the total distance travelled by the robot, this value being doubled if the robot finishes ahead of where it started. An additional bias was added for these experiments for walking in the forward direction, by adding a value directly proportional to the distance travelled forward (rather than any other direction) to the original computed fitness. This was to counteract the robot travelling (albeit quite effectively) in a sideways direction, a pattern exacerbated by the increased stability of the Bioloid robot as opposed to its QRIO-like counterpart. Because of its importance the field specifying the maximum joint ranges is increased from 8 to 16 bits. Also, an additional four 16-bit fields define the speed of movement for each of the four keyframes. This brings the total genome length to 400 bits (two of the 20 motor fields are left unused). The population size is correspondingly increased from 80 to 100 to accommodate this increase in genome length. While each robot starts its run from the same fixed position, it inherits the initial values for its joints from the final position of the joints in the previously evaluated robot; the first robot of the following generation, which was guaranteed safe passage by the elitist mechanism, inherits the starting positions of its joints from the final position of the joints of the last robot of the previous generation. This ensures a degree of robustness in the walks generated by the evolutionary process; also because of this the maximum fitness values from generation to generation can fall as well as rise. Our previous work involved evolving a subset of the Bioloid robots' joints (Eaton, 2007), however a recent upgrade of the Webots software allowing for the detection of internal collisions has allowed us to extend the evolution to the full 18 joints of the Bioloid humanoid.

Fig.5 shows the maximum and average fitness together with the allowed joint range averaged over three runs for the 18-DOF simulated Bioloid humanoid. We see that around generation 150 the maximum fitness begins an approximately linear increase as walking patterns develop; after generation 250 this corresponds to quite a stable walk in the forward direction. Fig.6 shows a walk evolved in the Webots simulator and Fig.7 demonstrates this walk as transferred to the Bioloid humanoid. This walk corresponds to a quite rapid but slightly unstable walk in the forward direction. The transfer to the real robot is not perfect due to some small inconsistencies between the Webots model and the actual robot

indicating work remains to be done to fully "cross the reality gap" (Lipson et al., 2006) but our current results are very promising.

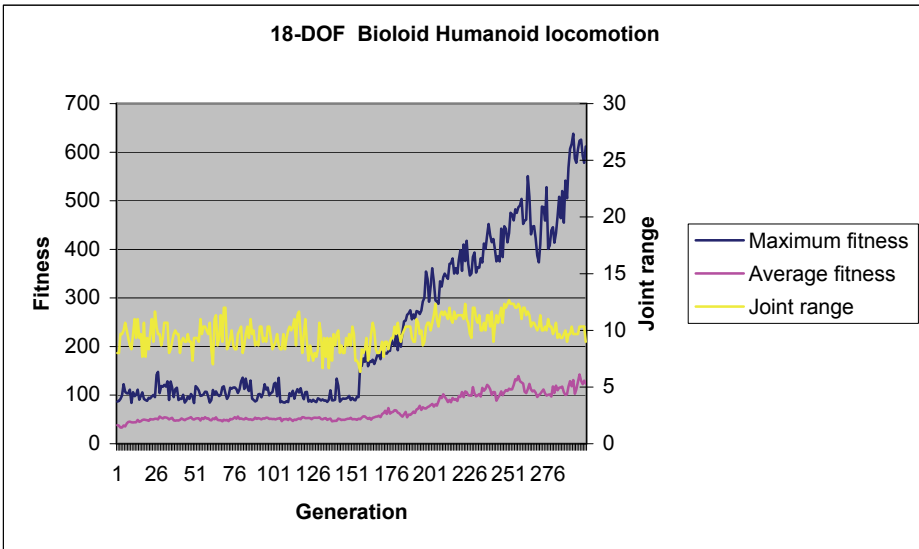


Figure 5. Maximum fitness, average fitness and joint range averaged over 3 runs for the 18-DOF Bioloid humanoid

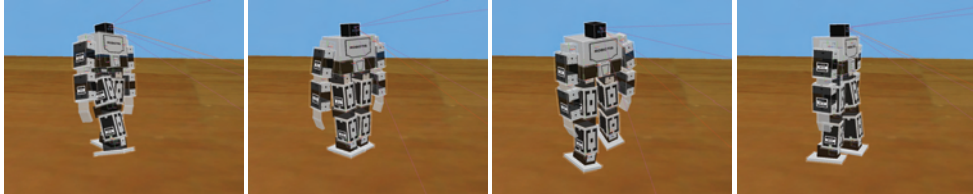


Figure 6. An evolved walk for the Bioloid humanoid

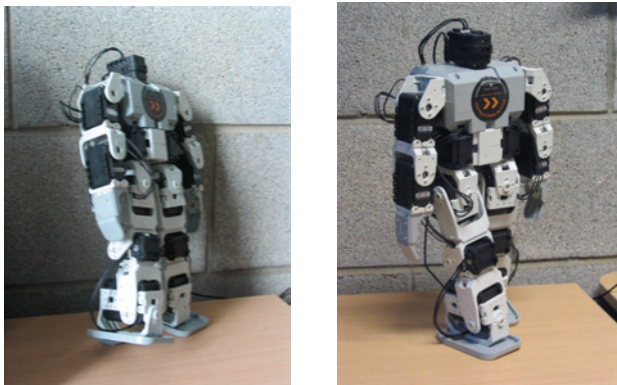


Figure 7. Two keyframe values for the evolved walk as transferred to the real robot

8. Discussion and conclusions

Following an initial introduction to the twin topics of evolutionary robotics and humanoid robotics, we discussed their recent convergence in the new field of evolutionary humanoid robotics. After presenting a survey of recent work in this field by other researchers, we introduced our own work in the area of evolving bipedal locomotion in a simulated high-DOF humanoid. After a brief discussion on the important topic of benchmarking future mobile robot performances we introduced our current hardware platform, and the implementation of locomotion, evolved in simulation using the Webots simulator, on the Bioloid platform for an 18-DOF humanoid robot. Advantages of our approach include its adaptability and the ability to generate life-like behaviours without the provision of detailed domain knowledge. While certain questions remain to be addressed, including the potential scalability of this approach to the generation of highly complex behaviours, the field of evolutionary humanoid robotics should prove a useful and powerful tool for future designers of humanoid robots.

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