First Three Generations of Evolved Robots

Jordan B. Pollack, Hod Lipson, Pablo Funes, and Gregory Hornby

Computer Science Dept.,
Brandeis University,
Waltham,
MA 02454, USA
pollack@cs.brandeis.edu

Abstract. The field of robotics today faces an economic predicament: most problems in the physical world are too difficult for the current state of the art. The difficulties associated with designing, building and controlling robots have led to a stasis, and robots in industry are only applied to simple and highly repetitive manufacturing tasks. Over the last few years we have been trying to address this challenge through an alternative approach: Rather than a seeking an intelligent general-purpose robot, we are seeking the process that can automatically design and fabricate special purpose mechanisms and controllers to achieve specific short-term objectives. This short paper provides a brief review of three generations of our research results. Automatically designed high part-count static structures that are buildable, automatically designed and manufactured dynamic electromechanical systems, and modular robots automatically designed through generative encoding. We expect that with continued improvement in simulation, manufacturing, and transfer, we will achieve the ability to automatically design and fabricate custom machinery for short-term deployment on specific tasks.

1 Roboeconomics

The field of Robotics today faces a practical economic problem: Flexible machines with minds cost so much more than manual machines and their humans operators. Few would spend $2K on a vacuum cleaner when a manual one is $200, or half a million dollars on a driverless car when a regular car is $20K, plus $\$6\frac{1}{2}$ per hour for its driver. The high costs associated with designing, building and controlling robots have led to a stasis [29] and robots in industry are only applied to simple and highly repetitive manufacturing tasks. Even though sophisticated teleoperated machines with sensors and actuators have found important applications (exploration of inaccessible environments for example), they leave very little decision, if at all, to the on-board software [30]

The central issue addressed by our work is a low cost way to get a higher level of complex physicality under control. We seek more controlled and moving mechanical parts, more sensors, more nonlinear interacting degrees of freedom — without entailing both the huge fixed costs of human design and programming and the variable costs in manufacture and operation. We suggest that this can

T. Gomi (Ed.): ER 2001, LNCS 2217, pp. 62–71, 2001.
© Springer-Verlag Berlin Heidelberg 2001

be achieved only when robot design and construction are fully automatic, and the results are inexpensive enough to be disposable.

Traditionally, robots are designed on a disciplinary basis: Mechanical engineers design complex articulated bodies, with state-of-the-art sensors, actuators and multiple degrees of freedom. These elaborate machines are then thrown over the wall to the control department, where software programmers and control engineers struggle to design a suitable controller. Even if an intelligent human can learn to control such a device, it does not follow that automatic autonomous control can be had at any price. Humans drastically underestimate animal brains: Looking into nature we see animal brains of very high complexity, brains more complex than the bodies they inhabit, controlling bodies which have been selected by evolution precisely because they were controllable by those brains. In nature, the body and brain of a horse are tightly coupled, the fruit of a long series of small mutual adaptations — like chicken and egg, neither one was designed first. There is never a situation in which the hardware has no software, or where a growth or mutation — beyond the adaptive ability of the brain — survives. The key is thus to evolve both the brain and the body, simultaneously and continuously, from a simple controllable mechanism to one of sufficient complexity for a particular specialized task.

The focus of our research is how to automate the integrated design of bodies and brains using a co-evolutionary learning approach. The key is to evolve both the brain and the body — simultaneously — from a simple controllable mechanism to one of sufficient complexity for a task. Within a decade we see three technologies that are maturing past threshold to make this a possible new industry. One is the increasing fidelity of advanced mechanical design simulation, stimulated by profits from successful software competition [35]. The second is rapid, one-of-a-kind prototyping and manufacture, which is proceeding from 3D plastic layering to stronger composite and metal (sintering) technology [8]. The third is our understanding of coevolutionary machine learning in design and intelligent control of complex systems, which is the primary specialty of our laboratory [1,19,32].

2 Coevolution

Coevolution, when successful, dynamically creates a series of learning environments each slightly more complex than the last, and a series of learners which are tuned to adapt in those environments. Sims' work (1994) on body-brain coevolution and the more recent Framsticks simulator [22] demonstrated that the neural controllers and simulated bodies could be coevolved. The goal of our research in coevolutionary robotics is to replicate and extend results from virtual simulations like these to the reality of computer designed and constructed special-purpose machines that can adapt to real environments. We are working on coevolutionary algorithms to develop control programs operating realistic physical device simulators, both commercial-off-the-shelf and our own custom simulators, where we finish the evolution inside real embodied robots. We are

ultimately interested in mechanical structures that have complex physicality of more degrees of freedom than anything that has ever been controlled by human designed algorithms, with lower engineering costs than currently possible because of minimal human design involvement in the product.

It is not feasible that controllers for complete structures could be evolved (in simulation or otherwise) without first evolving controllers for simpler constructions. Compared to the traditional form of evolutionary robotics [6,9,13,21,27] which serially downloads controllers into a piece of hardware, it is relatively easy to explore the space of body constructions in simulation. Realistic simulation is also crucial for providing a rich and nonlinear universe. However, while simulation creates the ability to explore the space of constructions far faster than real-world building and evaluation could, there remains the problem of transfer to real constructions and scaling to the high complexities used for real-world designs.

3 Research Products

We describe three major projects in achieving Fully Automated Design (FAD) and manufacture of high-parts-count autonomous robots. The first is evolution inside simulation, but in simulations more and more realistic so the results are not simply visually believable, as in Sims' work (1994), but also buildable. We investigated transferring evolved high part-count, static structures from simulation to the real world. The second is to evolve automatically buildable dynamic machines that are nearly autonomous in both their design and manufacture. The third thrust, and perhaps hardest, addresses scaling to more complex tasks: handling complex, high part-count structures through modularity. We have preliminary and promising results in each of these areas, which we outline below. Further work in automatic manufacturing, sensor integration, and task specification will follow.

3.1 Evolving Buildable Mechanical Simulations (Legobots)

The idea of evolving mechanical structures inside simulation is not new, and Commercial CAD simulation systems are exciting, yet not constrained enough for the products to be buildable, because a human provides numerous constraints to describe reality. In order to evolve both the morphology and behavior of autonomous mechanical devices that can be built, one must have a simulator that operates under many constraints, and a resultant controller that is adaptive enough to cover the gap between the simulated and real world. Features of a simulator for evolving morphology are:

- Representation — should cover a universal space of mechanisms.
- Conservative — because simulation is never perfect, it should preserve a margin of safety.
- Efficient — it should be quicker to test in simulation than through physical production and test.
- Buildable — results should be convertible from a simulation to a real object.

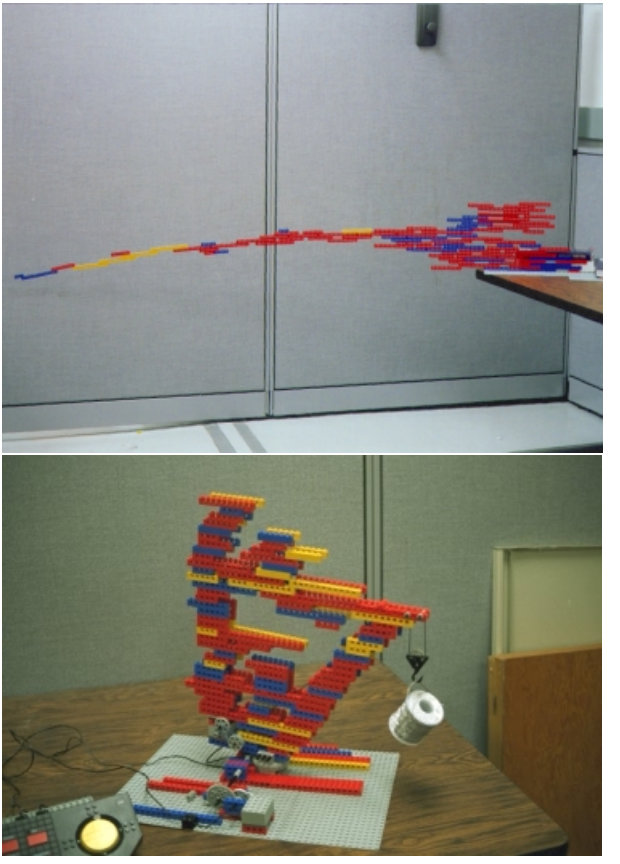


Fig. 1. Evolved Cantilevered Bridge, and Triangular Crane. Only Static components are fully designed by evolutionary algorithms.

One approach is to custom-build a simulator for modular robotic components, and then evolve either centralized or distributed controllers for them. In advance of a modular simulator with dynamics, we recently built a simulator for (static) Lego bricks, and used very simple evolutionary algorithms to create complex Lego structures, which were then manually constructed ([10]-[12]). Our model considers the union between two bricks as a rigid joint between the centers of mass of each one, located at the center of the actual area of contact between them. This joint has a measurable torque capacity. That is, more than a certain amount of force applied at a certain distance from the joint will break the two bricks apart. The fundamental assumption of our model is this idealization of the union of two Lego bricks. The genetic algorithm reliably builds structures that meet simple fitness goals, exploiting physical properties implicit in the simulation. Building the results of the evolutionary simulation (by hand)

demonstrated the power and possibility of fully automated design. The long bridge of Figure 1 shows that our simple system discovered the cantilever, while the weight-carrying crane shows it discovered the basic triangular support.

3.2 Genetically Organized Lifelike Electro Mechanics (GOLEM)

The next step is to add dynamics to modular buildable physical components, and to insert their manufacturing constraints into the evolutionary process. We are experimenting with a new process in which both robot morphology and control evolve in simulation and then replicate automatically into reality [24]. The robots are comprised of only linear actuators and sigmoidal control neurons embodied in an arbitrary thermoplastic body. The entire configuration is evolved for a particular task and selected individuals are printed pre-assembled (except motors) using 3D solid printing (rapid prototyping) technology, later to be recycled into different forms. In doing so, we establish for the first time a complete physical evolution cycle. In this project, the evolutionary design approach assumes two main principles: (a) to minimize inductive bias, we must strive to use the lowest level building blocks possible, and (b) we coevolve the body and the control, so that they stimulate and constrain each other. We use arbitrary networks of linear actuators and bars for the morphology, and arbitrary networks of sigmoidal neurons for the control. Evolution is simulated starting with a soup of disconnected elements and continues over hundreds of generations of hundreds of machines, until creatures that are sufficiently proficient at the given task emerge. The simulator used in this research is based on quasi-static motion. The basic principle is that motion is broken down into a series of statically-stable frames solved independently. While quasi-static motion cannot describe high-momentum behavior such as jumping, it can accurately and rapidly simulate low-momentum motion. This kind of motion is sufficiently rich for the purpose of the experiment and, moreover, it is simple to induce in reality since all real-time control issues are eliminated. Several evolution runs were carried out for the task of locomotion. Fitness was awarded to machines according to the absolute average distance traveled over a specified period of neural activation. The evolved robots exhibited various methods of locomotion, including crawling, ratcheting and some forms of pedalism (Figure 2. Selected robots are then replicated into reality: their bodies are first fleshed to accommodate motors and joints, and then copied into material using rapid prototyping technology (Figure 3). Temperature-controlled print head extrudes thermoplastic material layer by layer, so that the arbitrarily evolved morphology emerges pre-assembled as a solid three- dimensional structure without tooling or human intervention. Motors are then snapped in, and the evolved neural network is activated (Figure 4. The robots then perform in reality as they did in simulation.

3.3 Evolving Modularity with Generative Encodings (Tinkerbots)

The main difficulty for the use of evolutionary computation for design is that it is doubtful whether it will reach the high complexities necessary for practical engineering. Since the search space grows exponentially with the size of

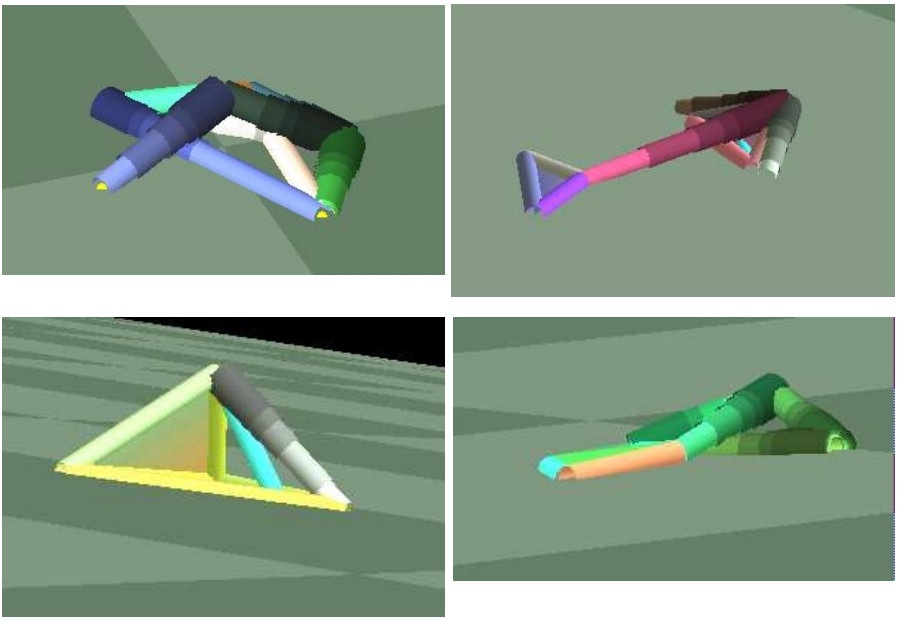


Fig. 2. Several different GOLEM's, evolved in simulation. Brains not shown. See http://demo.cs.brandeis.edu/golem

the problem, search algorithms that use a direct encoding for designs will not scale to large designs. An alternative to a direct encoding is a generative specification, which is a grammatical encoding that specifies how to construct a design, [33,2]. Similar to a computer program, a generative specification can allow the definition of re-usable sub-procedures allowing the design system to scale to more complex designs than can be achieved with a direct encoding. Ideally an automated design system would start with a library of basic parts and would iteratively create new, more complex modules, from ones already in its library. The principle of modularity is well accepted as a general characteristic of design, as it typically promotes decoupling and reduces complexity [36]. In contrast to a design in which every component is unique, a design built with a library of standard modules is more robust and more adaptable [25]. Our system for automated modular design uses Lindenmayer systems (L-systems) as the genotype evolved by the evolutionary algorithm. L-systems are a grammatical rewriting system introduced to model the biological development of multicellular organisms. Rules are applied in parallel to all characters in the string just as cell divisions happen in parallel in multicellular organisms. Complex objects are created by successively replacing parts of a simple object by using the set of rewriting rules. Using this system we have evolved 3D static structures [15], and locomoting mechanisms [14]. Figure 5 shows one of these robots is shown both in simulation and transferred successfully into reality [16].

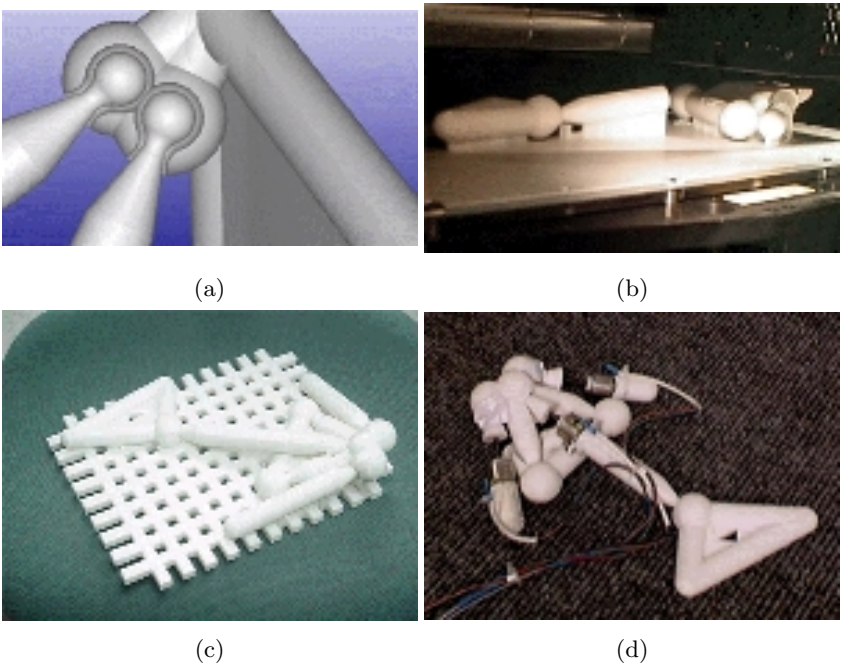


Fig. 3. (a) Fleshed joints, (b) replication progress, (c) pre-assembled robot (d) final robot with assembled motors. See http://demo.cs.brandeis.edu/golem

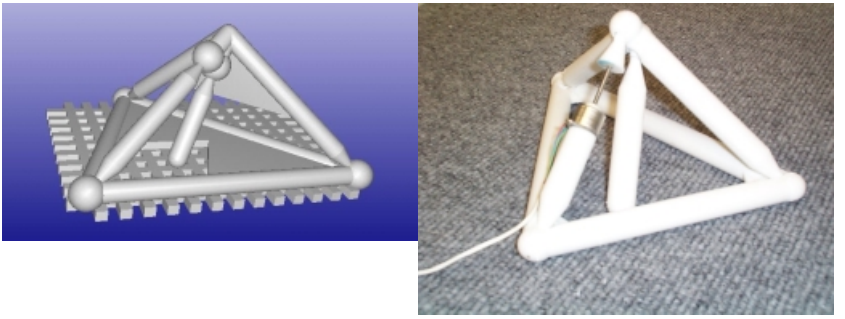


Fig. 4. The geometric representation of a robot, and the actual fabricated machine. Motors are snapped in by hand, and the controller is loaded into a microcontroller chip.

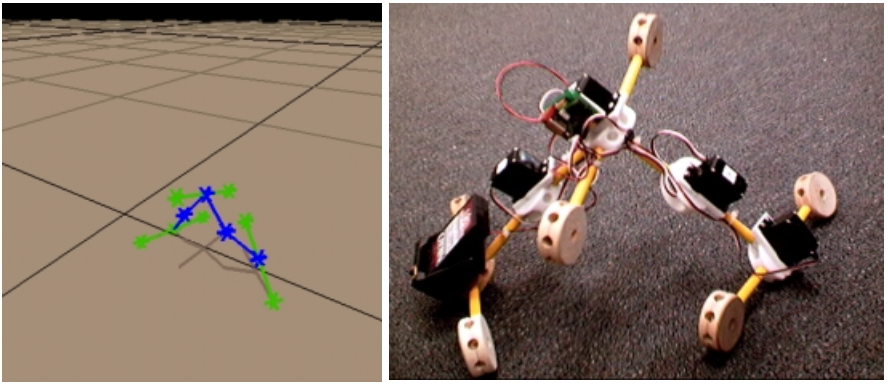


Fig. 5. A virtual "tinkerbot" and the real thing. These robots are evolved with L-systems, and constructed from a fixed collection of parts.

4 Conclusion

Can evolutionary and coevolutionary techniques be applied to real physical systems? In this paper we have presented a selection of our work each of which addresses physical evolutionary substrate in one or more dimensions. We have overviewed research in use of simulations for handling high part-count static structures that are buildable, dynamic electromechanical systems with complex morphology that can be built automatically, and generative encodings as a means for scaling to complex structures. Our long-term vision is that both the morphology and control programs for robots arise directly through morphology and control-software coevolution: starting from primitive controllers attached to primitive bodies the evolutionary system scales to complex, modular creatures by increasing the dictionary of components as stored in the creature encoding. Our current research moves towards the overall goal down multiple interacting paths, where what we learn in one thrust aids the others. We envision the improvement of our hardware-based evolution structures, expanding focus from static buildable structures to buildable robots. We see a path from evolution inside CAD/CAM and buildable simulation, to rapid automatic construction of novel controlled mechanisms, and finally the use of generative encodings to achieve highly complex, modular individuals. We believe such a broad program is the best way to ultimately construct complex autonomous robots whose corporate assemblages consist of simpler, automatically-manufactured parts. Only when robots can economically justify their own existence will they become more ubiquitous outside repetitive industrial use.

Acknowledgements. This research was supported in part by the National Science Foundation (NSF), the office of Naval Research (ONR), and the Defense Advanced Research Projects Agency (DARPA).

References

1. Angeline P. J., Saunders G. M., and Pollack J. B.. An evolutionary algorithm that constructs recurrent networks. *IEEE Transactions on Neural Networks*, 5(1):54–65, 1994.
2. Bentley P. and Kumar S.. Three ways to grow designs: A comparison of embryogenies of an evolutionary design problem. In Banzhaf, Daida, Eiben, Garzon, Honavar, Jakiel, and Smith, editors, *Genetic and Evolutionary Computation Conference*, pages 35–43, 1999.
3. Bentley P. J.. Generic Evolutionary Design of Solid Objects using a Genetic Algorithm. PhD thesis, Division of Computing and Control Systems, School of Engineering, The University of Huddersfield, 1996.
4. Bentley P., editor. *Evolutionary Design by Computers*. Morgan-Kaufmann, San Francisco, 1999.
5. Brooks R.. Intelligence without representation. *Artificial Intelligence*, 47(1–3):139–160, 1991.
6. Cliff D., Harvey I, and Husbands P.. Evolution of visual control systems for robot. In M. Srinivisan and S. Venkatesh, editors, *From Living Eyes to Seeing Machines*. Oxford, 1996.
7. Cliff D., Noble J.. Knowledge-based vision and simple visual machines. Philosophical Transactions of the Royal Society of London: Series B, 352:1165–1175, 1997.
8. Dimos D., Danforth S.C., and Cima M.J.. *Solid freeform and additive fabrication*. In J. A. Floro, editor, 1998.
9. Floreano D. and Mondada F.. Evolution of homing navigation in a real mo-bile robot. *IEEE Transactions on Systems, Man, and Cybernetics*, 1996.
10. Funes P. and Pollack. J.B. Computer evolution of buildable objects. In Phil Husbands and Inman Harvey, editors, *Fourth European Conference on Artificial Life*, pages 358–367, Cambridge, 1997. MIT Press.
11. Funes P. and Pollack. J.B. Evolutionary body building: Adaptive physical designs for robots. *Artificial Life*, 4(4):337–357, 1998.
12. Funes P. and Pollack J. B.. Computer evolution of buildable objects. In Peter Bentley, editor, *Evolutionary Design by Computers*, pages 387 - 403. Morgan-Kaufmann, San Francisco, 1999.
13. Gallagher J. C., Beer R. D., Espenschield K. S., and Quinn R. D.. Application of evolved locomotion controllers to a hexapod robot. *Robotics and Autonomous Systems*, 19:95–103, 1996.
14. Hornby G. S., Lipson H., and Pollack J. B.. Evolution of generative design systems for modular physical robots. In *IEEE International Conference on Robotics and Automation*, 2001.
15. Hornby G.S. and Pollack J. B Body-brain coevolution using l-systems as a generative encoding. In *Genetic and Evolutionary Computation Conference*, 2001.
16. Hornby G.S. and Pollack J. B.. The advantages of generative grammatical encodings for physical design. In *Congress on Evolutionary Computation*, 2001.
17. Husbands P., Germy G., McIlhagga M., and Ives R.. Two applications of genetic algorithms to component design. In T. Fogarty, editor, *Evolutionary Computing*. LNCS 1143, pages 50–61. Springer-Verlag, 1996.
18. Jakobi N.. Evolutionary robotics and the radical envelope of noise hypothesis. *Adaptive Behavior*, 6(1):131–174, 1997.
19. Juillé H. and Pollack J. B.. Dynamics of co-evolutionary learning. In *Proceedings of the Fourth International Conference on Simulation of Adaptive Behavior*, pages 526–534. MIT Press, 1996.

20. Kane C. and Schoenauer M.. Genetic operators for two-dimentional shape optimization. In J.-M. Alliot, E. Lutton, E. Ronald, M. Schoenauer, and D. Snyers, editors, *Artificial Evolution — EA95*. Springer-Verlag, 1995.
21. Kawauchi Y., Inaba M., and Fukuda T.. Genetic evolution and self-organization of cellular robotic system. *JSME Int. J. Series C. (Dynamics, Control, Robotics, Design & Manufacturing)*, 38(3):501–509, 1999.
22. Komosinski M. and Ulatowski. S. Framsticks: Towards a simulation of a nature-like world, creatures and evolution. In Jean-Daniel Nicoud Dario Floreano and Francesco Mondada, editors, *Proceedings of 5th European Conference on Artificial Life (ECAL99)*, volume 1674 of Lecture Notes in Artificial Intelligence, pages 261–265. Springer-Verlag, 1999.
23. Lee W., Hallam J., and Lund H.. A hybrid gp/ga approach for co-evolving controllers and robot bodies to achieve fitness-specified tasks. In *Proceedings of IEEE 3rd International Conference on Evolutionary Computation*, pages 384–389. IEEE Press, 1996.
24. Lipson H and Pollack J.B.. Automatic design and manufacture of robotic lifeforms. *Nature*, 406(6799):974–978, 2000.
25. Lipson, H., Pollack J. B., Suh N. P., 2001, "Promoting Modularity In Evolutionary Design", *Proceedings of DETC'01 2001 ASME Design Engineering Technical Conferences*, September 9–12, 2001, Pittsburgh, Pennsylvania, USA, to appear.
26. Lund H., Hallam J., and Lee W.. Evolving robot morphology. In *Proceedings of IEEE Fourth International Conference on Evolutionary Computation*, pages 197–202. IEEE Press, 1997.
27. Lund H.. Evolving robot control systems. In Alexander, editor, *Proceedings of 1NWGA*. University of Vaasa, 1995.
28. Maja J Mataric and Dave Cliff. Challenges in evolving controllers for physical robots. *Robotics and Autonomous Systems*, 19(1):67–83, 1996.
29. Moravec H.P.. Rise of the robots. *Scientific American*, pages 124–135, December 1999.
30. Morrison K. and Nguyen. T., On-board software for the mars pathfinder microrover. In *Proceedings of the Second IAA International Conference on Low-Cost Planetary Missions*. John Hopkins University Applied Physics Laboratory, April 1996.
31. Nilsson N. J.. A mobile automaton: An application of artificial intelligence techniques. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pages 509–520, 1969.
32. Pollack J.B. and Blair A. D.. Coevolution in the successful learning of backgammon strategy. *Machine Learning*, 32:225–240, 1998.
33. Schoenauer M.. Shape representations and evolution schemes. In L. J. Fogel, P. J. Angeline, and T. Back, editors, *Proceedings of the 5th Annual Conference on Evolutionary Programming*. MIT Press, 1996.
34. Sims K. Evolving 3d morphology and behavior by competition. In R. Brooks and P. Maes, editors, *Proceedings 4th Artificial Life Conference*, pages 28–39. MIT Press, 1994.
35. Sincell M.. Physics meets the hideous bog beast. *Science*, 286(5439):398–399, October 1999.
36. Suh N. P.. *The Principles of Design*. Oxford University Press, 1990.