Chapter 3
Why Evolutionary Robotics Will Matter

Kenneth O. Stanley

Abstract. While at present Evolutionary Robotics (ER) is generally not studied in mainstream robotics, the main idea in this article is that ER has the opportunity to gain relevance by taking seriously its natural inspiration. The chasm that separates the behavior of robots today from the robustness and fluidity of organisms in nature is most naturally addressed by an approach that indeed respects the process through which such organisms originated. Yet the challenge is to identify the elusive missing ingredient that would allow ER to realize its full potential.

3.1 Joining the Mainstream

Evolutionary Robotics (ER) is not a mainstream topic in robotics. It is easy to find syllabi for "Introduction to Robotics" courses on the Internet without even a mention of ER in the entire semester schedule. Yet ER *should* be important to robotics as an active subcommunity that aims to address many of the same challenges. The question is how this divide between mainstream robotics and ER will ultimately be bridged. This article attempts to address this question by looking mainly forward toward the promise of ER and how that promise will make it increasingly relevant to robotics as a whole.

An important goal for robotics in general is to avoid the stereotypical stilted, jittery motion of awkward machines and move instead towards fluid, natural behaviors. In this light, it is interesting to note the tools with which mainstream robotics proposes to address this challenge. The 2007 *Introduction to Robotics* syllabus at Stanford University [7] gives a sense of what these tools are in the mainstream view: spatial descriptions, forward kinematics, Jacobians for velocities and static forces, computer vision, inverse kinematics and trajectory generation, acceleration and inertia, dynamics, PID control, joint space control, operational space control,

Kenneth O. Stanley
Department of Electrical Engineering and Computer Science,
University of Central Florida, Orlando, FL 32816 USA
e-mail: kstanley@cs.ucf.edu

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and force control. Note that nowhere in the syllabus is ER mentioned. The classic ER book *Evolutionary Robotics* [12] is rarely cited as a textbook or even an auxiliary reference in robotics courses either. The day when ER genuinely impacts robotics and not only evolutionary computation remains ahead.

Yet even a cursory look at nature hints at why ER does have the potential for dramatic impact. After all, every organism on Earth is the product of *evolution*, and no robot yet created through conventional means even comes close to the stealth of a lion, the grace of a bird, or the balance of a human. Even in simulation such capabilities are not convincingly reproduced, so it is not just a matter of mechanical limitation. Both the robustness and fluidity of natural movement remain symbols of how far we have to go.

For example, when a human sprains an ankle, he or she may walk with a limp, but the entire motor system recalibrates almost instantaneously to compensate for the disability without the risk of falling. Throughout childhood the body changes in height and proportion, yet walking remains seamless. At the same time, although it is a qualitative observation, the *fluidity* of natural movement is unmatched. One need only watch horses at play or monkeys swinging from branches to appreciate the gaping chasm between natural fluidity and robotics today.

If ER could produce robots with the same robustness and fluidity, it would earn its place as a canonical topic in mainstream robotics. Yet the problem is that ER does not presently produce such behavior any more than mainstream robotics does. For example, a survey of evolved bipeds, while impressive for the progress that it demonstrates so far, shows that the products of ER today are nevertheless still brittle and highly stereotyped compared to nature's flexible solutions [1, 6, 9, 14, 23].

3.2 Bridging the Gap

The future of ER lies in taking this achievement gap seriously. We need to acknowledge that when applied to robotics, evolutionary algorithms *should* produce artifacts that remind us of nature, which provides our primary inspiration for running evolution in the first place. That does not mean that human-level intelligence is necessary to achieve, but fluid motion and robustness belong more realistically within scope. If evolutionary computation can offer nothing else, at least it should offer that.

The almost-magical elegance and grace of the products of natural evolution is rarely acknowledged within the technical-minded confines of the research community yet nevertheless deserve our attention as a source of inspiration and indeed as a proof of what is possible through ER. It is exactly that magical ingredient that mainstream robotics seems to lack. That exquisite, seamless fluidity of motion that unfolds without apparent effort is a clue to what may be possible. By ignoring this elusive facet of life on Earth, mainstream robotics risks missing what ER is positioned to gain.

Then what does it mean that ER does not today exhibit that same magic? The answer is that ER is poised at the brink of opportunity; the essential prerequisite to our progress as a field is to acknowledge that something fundamental is missing. Yet whatever that missing ingredient is, it is closer to our purview than to the traditional tools of mainstream robotics. Rather than a negative sentiment, acknowledging this missing link suggests a profound opportunity for change just over the horizon.

3.3 Realizing the Promise

Of course, the natural next question is what shape that change may take. Someday, we should hope to evolve e.g. a single biped (or quadruped) neurocontroller that works in almost *any* biped morphology, just as our brains allow us to walk as our body grows and changes. Rather than starting life walking right away, as almost every evolved biped does today [1, 6, 9, 14, 23], it should learn on its own the dimensions and dynamics of its new body and rise from the ground to walk after some experimentation. In effect, the hypothesis is that the robustness and fluidity of nature is earned at the expense of a period of adaptation and habituation that occurs early in life, just as babies learn to walk.

If this hypothesis is right, it suggests that adaptation, which in artificial neural networks follows from synaptic plasticity, may be an important part of any model that approaches the elusive superiority of nature. Yet synaptic plasticity remains an open area of investigation in neuroevolution [2, 4, 11, 13, 17, 18, 19, 20]. Recent work in our research group aims to combine synaptic plasticity with the indirect encoding in HyperNEAT [5, 21], which would allow regular patterns of plasticity rules to be distributed across the network [15]. At present, although there is already precedent for incorporating synaptic plasticity into simple ER models (e.g. in controlling wheeled Khepera robots [4]), it has not yet been combined with controllers that must attempt feats like learning to walk with variable morphology during their lifetime.

In any case, simply combining neuroevolution [3, 22, 24] and synaptic plasticity alone is not a complete answer. The model of plasticity will likely need to be especially sophisticated and refined to be able to support unprecedented robustness. Furthermore, new computational abstractions of evolution may need to be developed that capture the open-ended process through which the products of nature were discovered [8, 10, 16]. Thus significant research lies ahead. Yet these research directions provide a hint of where opportunity may lie.

The important point for this article is that if we can evolve a controller that wakes up inside any body and learns to make it work, all without the need for any traditional analysis whatsoever, there is the potential to revolutionize mainstream robotics. It happened in nature and it should therefore be possible in ER. So while today some in the mainstream may see ER as unnecessary or suboptimal, its promise is in its inspiration, which encompasses the most robust robotic systems on Earth: *nature*.

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