Embodied Artificial Life at an Impasse

Can Evolutionary Robotics Methods Be Scaled?

Andrew L. Nelson, member IEEE
Androtics, LLC
Tucson, AZ USA
alnelson@ieee.org

***Abstract*—Evolutionary robotics (ER) investigates the application of artificial evolution toward the synthesis of robots capable of performing autonomous behaviors. Over the last 25 years, researchers have reported increasingly complex evolved behaviors, and have compiled a de facto set of benchmark tasks. Perhaps the best known of these is the obstacle avoidance and target homing task performed by differential drive robots. More complex tasks studied in recent ER work include augmented variants of the rodent T-maze and complex foraging tasks. But can proof-of-concept results such as these be extended to evolve complex autonomous behaviors in a general sense? In this topical analysis paper we survey relevant research and make the case that common tasks used to demonstrate the effectiveness of evolutionary robotics are not characteristic of more general cases and in fact do not fully prove the concept that artificial evolution can be used to evolve sophisticated autonomous agent behaviors. Robots capable of performing many of the tasks studied in ER have now been evolved using nearly aggregate binary success/fail fitness functions. However, arguments used to support the necessity of incremental methods for complex tasks are essentially sound. This raises the possibility that the tasks themselves allow for relatively simple solutions, or span a relatively small candidate solution set. This paper presents these arguments in detail and concludes with a discussion of current ER research.**

Keywords—evolutionary robotics; artificial life; artificial evolution; open-ended evolution; genetic algorithms

I. Introduction

This paper examines the possibility that artificial evolutionary methods used in evolutionary robotics (ER), while producing compelling results on a range of benchmark tasks and behaviors of moderate difficulty, may not generalize to complex useful tasks. Although recent advancements, including the use of multiobjective optimization approaches as well as task-independent diversity maintenance methods, are likely to extend the range of evolvable ER behaviors by perhaps as much as an order of magnitude (reviewed in [1]), there remain fundamental difficulties in combining evolutionary methods inspired by nature with goal-driven searches.

The body of ER research reported in the literature traces the development of methodologies for evolving agents capable of specific tasks of modest difficulty. The sophistication of tasks continues to increase, but much more slowly than might be expected from the exponential explosion of computing power seen in the last two decades. One of the more complex tasks reported to date is a foraging task presented in [2]. In this task a robot collects balls in one room and delivers them to a specific goal location in another. The robot controllers must evolve all low level competencies, including object avoidance and ball collection and delivery, hence the task includes a significant level of behavior acquisition and integration. The most complex ER tasks may fall into the range of minimal cognition as set out by Beer [3]. However, all ER control tasks studied to date can be solved by relatively simple algorithms. The body of ER research represents only limited progress toward the elusive goal of artificial evolution-based automatic acquisition of general behaviors for agents situated in complex environments. There is now, and has been for the last decade, considerable pressure in the ER community to generate controllers capable of demonstrably complex behaviors. Within this context, and considering that benchmark ER tasks have in most cases been studied and reproduced many times, researchers and theorists have begun to ask why it is the case that ER methods have not produced complex situated agents [4-6].

The application of natural selection to configure artificial agents to perform specific complex autonomous behaviors appears to be much more problematic than had been generally recognized [7-11]. In the larger field of Artificial Life (ALife) there has been a move toward characterizing the conditions under which open-ended evolution [12] can occur [6, 13, 14]. This in turn has added steam to a growing realization that the fitness or objective functions used to drive the artificial evolution of agents (robots in the case of ER) may be incompatible with open-ended evolution [8, 15, 16]. Although evolution is popularly characterized by the phrase “survival of the fittest”, it has been pointed out by theoreticians and researchers that conceptualizing fitness as a driving force does not fully describe natural evolution [7, 15, 16]. Natural evolution is a goalless process, in the most general sense, but local adaptation can often be modeled satisfactorily in terms of genotype or phenotype features and reproductive efficiency as formalized by a fitness landscape, as per Sewall Wright [17, 18]. Here, though, local adaptation as observed in nature is more akin to optimization, and does not readily translate into a process that can synthesize artificial agents capable of specific sophisticated behaviors in complex environments.

Issues related to modeling natural evolution have serious implications for ALife in general [12, 19]. In ER, by contrast, a specific behavior is usually sought, and hence there is often a definable goal at least at a high level [1, 20]. But this raises another difficulty: even with a well-defined goal, formulating a goal-oriented fitness function capable of traversing a vast ultra-high-dimensional search space is likely to be intractable for complex tasks without the aid of detailed domain knowledge [21]. Functions that aggregate fitness evaluation based on success or failure to complete a task suffer from the inability to generate any fitness signal in randomly initiated populations [22, 23]. For goal-driven evolutionary searches for behaviors of sufficient complexity, fitness functions that do not encode significant features of a particular solution will tend to define fitness landscapes in which regions outside a given radius of any fitness optimum consist primarily of plateaus with no detectable gradient (the Bootstrap Problem). Incremental evolution and shaping methods require increasingly more specific domain knowledge, limiting their use to problems where such information is obtainable. In a broad sense, artificial evolutionary schemes that drive selection by coupling performance of a specific task with survival are forms of optimization as opposed to synthesis [24]. As tasks become more complicated, requiring greater numbers of components and complex interactions, optimization methods contribute less to overall problem solutions and approach a purely refinement-oriented utility.

In this paper, we look at several lines of reasoning that support the view that ER methods will not scale without substantial changes. As summarized above, current fitness assessment methods are likely to have significant problems in complex ER domains. Also, we contend that canonical ER test problems can be solved by optimization methods and aren't representative of arbitrarily complex cases. We then touch on a few more esoteric challenges to ER. For instance, the success that ER has demonstrated to date might be due to a functional similarity between synthesis and optimization methods that holds for simple problems but not for complex problems. Further, certain aspects of how humans conceptualize and model complex systems may add to difficulties in designing artificial evolution-based platforms [9, 11, 25].

The lack of progress in ER may not be solely due to theoretical problems. Doncieux and Mouret [1] review recent advances in ER methods in a survey of selective pressures used in evolution. These include diversity maintenance methods [2, 26-28] and the use of multiobjective optimization methods [29, 30]. Very large populations, situated asynchronous genetic algorithms (GAs) [31] and/or task-independent diversity-maintaining mechanisms coupled with increases in computing power could lead to an order of magnitude increase in the complexity of achievable tasks. Even so, we contend that task-specific goal-driven evolution does not scale generally, and will eventually come up against a hard ceiling in terms of achievable complexity. Advancement beyond that point will require augmentation of basic ER methodologies with fusion and decomposition techniques [5, 32, 33].

In the remainder of this paper, Section II summarizes the origins and rise of embodied artificial life as a research field. Sections III and IV summarize and classify tasks/behaviors studied in ER and fitness functions used to drive the evolution of these behaviors. Sections V and VI respectively contain discussions of the emerging challenges in ER and recent research efforts to overcome these challenges.

II. Background and History

Creating evolving self-replicating machines capable of long-term adaptation has been an enticing goal of artificial intelligence researchers since the earliest days of the computer age. Famously, John Von Neumann [34] introduced and formulated the concept of autonomous self-replicating machines. Recognition that computers could duplicate and harness some aspects of Darwinian evolution to solve difficult problems also has its roots at the dawn of the computer age. Evolution-based computing methods were even considered as rivals to procedural programming in the late 1940's and early 1950's [35, 36]. One work in particular, performed by Friedman [37] in the 1950's, used a form of artificial evolution to evolve simulated robots to perform a chemo-gradient following task. This work foreshadowed by more than thirty years the rise of situated agent-based artificial life [38-41] and its embodied counterpart, evolutionary robotics [42-49].

The decade spanning the 1990's could be considered the heyday of early evolutionary robotics. Many of the now standard test scenarios were developed and extensively explored during this time. These include navigation with obstacle avoidance and target homing [50, 51], foraging [7], differential navigation with memory [52], gait learning in legged robots [44, 53], coevolution of morphology and control for locomotion [54], and pursuit and evasion, usually formulated in terms of coevolution of populations [38, 39, 55].

ER research from the 1990's relied mainly on hand-formulated fitness functions that defined many specific features of the behaviors for which the robots were being evolved. In the following decade, many of these tasks were revisited and robots were evolved using much less a priori information in the selection process. During this time period a series of more elaborate behaviors were evolved in larger environments, using color vision for sensing or requiring greater use of memory (see for example [23, 56, 57]). There were also advancements in methodologies, including refinement of real-robot coupled simulators, evolutionary neural networks, and coevolution of morphology and control [54]. The latter has progressed from the simulated block creatures in [40] to agents evolved in simulation and constructed in the physical world (see [58] for a review).

Recently there have been additional advances in ER in terms of complexity of behavior [2, 30, 32, 33, 59-62]. We will look at some of these in more detail in later sections of this paper. Some of these advances may represent the beginnings of a bridge to generalized evolution of competencies for complex autonomous agents, while others may be examples of special cases that take advantage of unusual task features to ramp up the power of evolutionary selection. The next two sections summarize tasks investigated in ER and fitness assessment methods and provide a context for the discussion that follows.

III. Benchmark Tasks

Replication of results, refinements in methods and comparative analyses make up the vast majority of published ER work. Approximately 100 separate research efforts are reviewed in [20]. These in turn entail several thousand published reports. Of these, though, there are only a few dozen distinct experiments in terms of the task or behavior investigated. These might be thought of as a de facto set of benchmark ER tasks and are summarized in this section. These tasks, along with several more complex behaviors discussed in Section VI, represent an assessment of the current level of complexity of evolved behaviors reported in the ER literature.

A. Target Homing

Target homing in environments containing occluding obstacles has been one of the most frequently investigated behaviors in ER. Early on, Harvey et al. studied locomotion with object avoidance [63] (also see [48]). Zone homing behaviors were evolved in [42]. Locomotion with homing was investigated in [46, 47]. In later research these behaviors were combined, so that evolving populations were required to master all of the necessary sub-skills as well as the ultimate target homing ability [50, 51, 64]. There are several variants on this basic theme. In [23] teams of robots competed in the same extended maze arena to locate goals differentially and in [57] a complex environment-mediated differential homing/repulsion task was studied (see Section VI.A).

B. T-maze

In recent years researchers have injected an element of forced memory into target homing tasks. This often takes the form of a rodent T-maze [52]. A standard T-maze may be equipped with two signal stations separated both from each other (either spatially or temporally) and from the T intersection (the memory-T-maze) [65, 66]. A complex version of this experiment, the double T-maze [32], is discussed in Section VI.A of this paper.

C. Foraging

Object collection and deposition or foraging tasks in ER vary in degree of behavioral complexity [7, 56, 67]. In general, robots locate and collect objects, and then deposit them at goal locations. Foraging tasks contain an element of sequencing and are less easily performed by purely reactive controllers. Currently more complex foraging tasks are a focus in ER. Examples include the sequential ball collection and deposition task summarized in the introduction [2] and a large-scale 100-robot foraging task evolved with an environmentally situated GA [61].

D. Pursuit Evasion

Pursuit evasion or predator-prey behaviors have been studied in ALife and ER over the years [39, 40, 68]. Typically two populations of competing agents are coevolved, with agents from one population taking the role of pursuer and the other evolving evasion behaviors. The key motivation for studying these and similar tasks is that the coevolving populations may generate an adaptive fitness landscape that extends the duration of selective pressure (the Red Queen effect). However, as noted in [1] and others, coevolving populations can also enter into cycles of repeating competitive behaviors. More complex examples include [30] in which neural controllers are evolved for a task that combines pursuit and foraging.

IV. Goal-Oriented Fitness Functions

This section discusses fitness assessment and selection mechanisms employed in ER research. Fitness functions often include information about both the degree to which a given task was completed, and how to perform a given task (a priori task solution information). Both of these forms of information can bias evolving populations toward a known or partially known solution. In [20] fitness functions for ER were classified into several categories based on the degree of a priori task solution information contained within the fitness function. We condense this classification to three basic groups: aggregate (also referred to as all-in-one or success/failure selection), incremental methods, and tailored fitness functions.

A. Aggregate Success/Fail Selection

At the lower end of introduced bias are aggregate fitness functions, which base selection only on success or failure to fully perform a task, and not on degree of completion or on details of how the task was performed. Aggregate fitness functions are sometimes combined with disappearing bootstrap modes to provide fitness feedback early in evolution before any members of the evolving population are able to complete the task. Although bootstrap modes do not contribute to selection late in evolution, they may leave a historical contingency equivalent to a bias in evolved populations, so an aggregate fitness function combined with a strong bootstrap mode may not be essentially different from some incremental fitness assessment methods.

B. Incremental Fitness Functions

In terms of injected bias, at the opposite extreme from pure aggregate fitness functions are incremental fitness functions and robot shaping techniques. These employ a series of successively more difficult fitness functions (and in some cases environmental conditions) to gradually evolve robots toward the ability to perform a particular task. These methods essentially chart a path through the search space to a particular (behavioral) solution to a given task and can require substantial amounts of explicit and intuitive domain knowledge to formulate. Experimenters may take an engineering or design approach and break down complex tasks and behaviors into simpler modules that might then be put into a hierarchical behavioral control structure [32].

C. Tailored Fitness Functions

Tailored fitness functions reside somewhere between the two extremes of pure aggregate and incremental fitness functions. These may explicitly select for some specific features of a solution but leave others unspecified alongside a weighted aggregate success/fail component. As noted in [1], the integration of multiobjective optimization methodologies into ER has allowed for a much more nuanced approach to the definition of tailored fitness functions.

D. Additional Considerations and Current Methods

In genetic algorithms used in ER some aspects of selective pressure might not be related to the performance of a desired task, but rather, to non-task-related features of the search's progression through a search space. As discussed in more detail in Section VI, this topic represents an active area of ER research and is reflected in several lines of work considered in this paper, including diversity maintenance [1, 2] and novelty search [28].

V. CHALLENGES TO ER

We focus on two arguments regarding the prospects for generalizing ER methods. First, the de facto set of canonical ER test problems may not be representative of the general class of complex autonomous agent behaviors. Second, fitness functions typically used in ER have underlying theoretical difficulties that make their application to the evolution of complex behaviors very problematic. Subsections C and D discuss several more esoteric points.

A. Benchmark ER Tasks Don't Represent the General Case

This subsection argues that ER behaviors evolved to date using mainly goal-driven artificial evolution aren't representative of the general class of autonomous environmentally situated agent behaviors. If benchmark ER tasks do not in fact reflect the general domain of ER, successful demonstration of these tasks may have produced a false sense that goal-driven artificial evolution is more useful for general problem solving than it actually is.

ER experiments sometimes evolve relatively trivial solutions for tasks that researchers had intended to entail a higher level of complexity. For example, the T-maze has solutions that do not require memory [52, 69]. Similarly, many benchmark ER tasks may have algorithmically simple, but possibly very obscure, solutions that are not obvious to designers, but which evolutionary searches can find in what essentially amount to extended optimization processes. To see how this is at least theoretically possible, consider the nature of functional transforms: domains can be transformed via a change of variables, a representational transform, or by other means to make computations simpler (but often at the cost of convoluting the exact meaning of the computation). Laplace transforms are a classic example of this: differential operators in the time domain are transformed to algebraic operators in the complex frequency domain. Many classes of evolutionary neural networks have general computing abilities and can in theory perform domain transforms. It is plausible that networks and other generalized evolvable controllers span something akin to a pan-transformational space during evolutionary search, finding simple solutions to seemingly complex tasks, but only if such solutions exist.

One might ask, then, if goal-driven evolution is able to find simple solutions to seemingly complex problems, why wouldn't this be considered an overall benefit and validation of ER? After all, isn't this what natural evolution does? The problem is that the general class of cognitive behaviors, especially those that require complex nested information manipulation, likely do not have simple solutions in any domain. Further, many evolutionary biologists do not consider natural evolution to be a goal-driven process, so that the generative power of natural evolution cannot be related to the emergence of any particular predefined complex capability [11, 15, 16, 25].

If one were to assume that most situated agent behaviors have simple representations in some domain, then perhaps ER, using high-level goal-driven selection, would in fact be able to evolve situated agents for arbitrary tasks in complex environments. But this assumption seems untenable in the general case: if in one domain or another, a behavioral task has a very simple solution, then its ultimate complexity (as measured for example by its Shannon entropy or Kolmogorov complexity) is low.

We want also to make a clear distinction between the "AI of the gaps" argument (i.e. if an artificial system can do it, it must not be AI) and our argument. We contend that goal-driven evolution is a form of optimization, and that some seemingly complex tasks actually reduce to simple optimization problems in some domains (see above, and also Subsection C of this section). Importantly, though, tasks beyond a threshold level of complexity may not have forms in any domain that are amenable to solution via direct optimization.

A second objection to these arguments might be that just because some benchmark ER tasks ultimately have trivial solutions, doesn't mean that they do as a rule. However, many of these tasks have been shown directly to have relatively simple solutions. A common component of many ER experiments is to hand code controllers for comparison [23, 59, 77]. For the vast majority of tasks investigated in the literature, such hand coded controllers are in fact extremely simple, requiring only a few pages of code, yet are shown to be competitive with evolved controllers in most cases. Further, recent work showing that ER environments can be transformed into behavioral domains that are tractable to an exhaustive search may provide an explicit empirical demonstration that some ER tasks do not represent the degree of complexity that was initially associated with them. In [28] and in related work reported in [66] the authors demonstrate that in some behavioral domains, neural controllers can be evolved to perform a specific memory-based task (delayed memory T-maze) without any feedback on task performance. This was accomplished by constructing, via the use of artificial evolution, a library of extended behaviors covering an entire behavioral domain using only a behavioral difference measure. Such work demonstrates that given an appropriate transform (into a behavioral domain in this case) it is possible to automatically enumerate a whole class of minimally cognitive behaviors using evolutionary methods with at least some expectation that a given behavior will be in the enumerated set.

The contention that the progression of ER results simply reflects an ongoing incremental effort toward ultimate generality is countered by the very slow rate of increase of complexity of directly evolvable behaviors. From the chemotaxis simulated robot behavior achieved via GA-like methods in the 1950's [37] to today's state-of-the-art results, which are only marginally more complex than directly evolved behaviors from the late 1990's, development is at best linear.

B. *Fitness Functions Don't Scale*

Problems with task-specific fitness functions have become a prominent focus in ER research [2, 27, 28, 70]. This subsection looks at the major classes of fitness functions that were outlined in Section IV, concluding that most forms of task-specific fitness functions are ultimately limited to extended optimization in terms of utility.

Aggregate fitness functions are likely to suffer from the inability to detect any fitness signal in initial random populations as tasks increase in complexity. For some threshold of behavioral complexity, fitness functions that do not select for specific a priori known solutions will be increasingly associated with intractable search landscapes [21, 71]. In particular, such functions will define fitness landscapes that consist primarily of zero-plateaus with undetectably shallow gradients. This was known in the early days of ER. Initially it was argued that in order to evolve any but the most simplistic behaviors in robots, an incremental approach would be needed [72, 73]. In the long run, this is still likely to be the case, but has been less of an issue than might have been expected. Some of the more complex tasks discussed in the literature have successfully employed aggregate or nearly aggregate fitness functions [2, 56, 59, 61]. The ramifications of this are of interest and provide an additional point of support for the conjecture presented in the previous subsection of this paper: the set of benchmark tasks used in ER contain solutions that are less complex than previously supposed.

Incremental fitness functions and robot shaping methods require ever-increasing domain knowledge, and in the limit, approach engineered methods such as those demonstrated in [5] and [33]. Here, as an a priori solution to a task is specified in greater detail by designers, the GA serves an increasingly more optimization-like role. Hence, the automatic design capability often presented as a motivating factor in ER research becomes marginalized.

Tailored fitness functions can combine varying degrees of aggregate selection with task solution features, and can approach incremental and shaping methods. In this sense, difficulties associated with tailored fitness functions are not qualitatively distinct from those of aggregate or incremental fitness functions but fall somewhere in between these two extremes. However, in some cases tailored fitness functions can be more problematic than simple aggregate fitness functions. As task complexity increases, researchers may inadvertently introduce topological features into a fitness landscape that are detrimental to the search [21, 28, 71]. In [28] just such a tailored fitness function is compared to, and out-performed by, a behavioral diversity-driven evolutionary search, referred to as novelty search. The task studied was a maze navigation and goal homing behavior. The mazes included cul-de-sacs oriented so that approaching the goal would require backtracking. The tailored fitness function in this case used a term that minimized the distance between the robot and the goal location, thus introducing a tendency for evolving controllers to favor strategies in which robots became ensnared in the cul-de-sacs. The intent of the research was to demonstrate that novelty search methods could overcome such problems. In addition, though, the work demonstrated that assumed task solution information (i.e. moving continually closer to the target is a good way to ultimately approach it) can introduce local optima into fitness landscapes.

At what level of task complexity do goal-oriented fitness functions begin to lose utility in terms of synthesis? An exact formal answer to this question may be beyond the scope of evolutionary theory at present. Still, confining the scope of this question to tasks in which only success/fail aggregate fitness is used to drive evolution, current research appears to be approaching an empirical answer. In [2] the authors show that aggregate selection alone is not sufficient to evolve robots for a repetitive ball collection and deposition task (see Section I). But when augmented with a diversity measure, the aggregate fitness function was able to support the evolution of controllers able to perform the task. Several different measures of diversity were investigated, and at least one of them contained no task-specific information, and thus the aggregate fitness function could still be considered to be adequate in some sense to drive the evolution of this relatively complex behavior. In another very complex task in which a robot must first navigate through a room with obstacles, enter and negotiate a double T-maze, then return to the original room, the authors resorted to a structured hierarchical decomposition method, stating that an aggregate or even a single fitness function approach would not be sufficient [32, 33]. Considering that the task-independent diversity metric augmented approach has not yet been attempted on a task of this complexity, a hard limit on the utility of aggregate fitness has not yet been fully demonstrated. The field of ER could be characterized as being collectively in a déjà vu-like state with regard to attitudes in the mid 1990's in which early forms of incremental evolution were seen as obviously necessary. Now, though, perhaps such methods are in fact the only viable alternatives.

A final consideration on the subject of fitness functions: even with the advent of multiobjective optimization methods, there is no standard methodology for creating fitness functions in ER, and experimenters often put a considerable amount of effort into their design. Moreover, this design process is usually not detailed in published results. Thus, the human-directed heuristic and subjective design process associated with generating fitness functions remains a largely uncharacterized but still essential aspect of ER.

C. *Optimization Equals Synthesis, but only for Simple Tasks*

The arguments presented in this subsection overlap to a degree with those of subsection A, but take a different bent. Some evolved autonomous agent behaviors seem to display a degree of scalable complexity [2, 56, 60, 61], but this may partially reflect a functional overlap between synthesis and optimization (adaptation) processes at the lower end of task complexity. Here we suggest that controller configurations within a certain radius of a solution or optimum (in terms of distance in genome space, i.e., Hamming distance, or phenome space) can be evolved using essentially local adaptation. If the task for which controllers are being evolved is simple enough, this radius might encompass a considerable portion of the entire search space. Hence, the chances of having a candidate solution with some detectable level of performance in a randomly initiated population might be greater than expected based on a superficial assessment of apparent task complexity.

This overlap between synthesis and optimization at the lower end of complexity is mediated by population size, diversity, and GA features, so that incremental improvements in evolvability can be demonstrated so long as Moore's law holds. For example, the ruggedness of a fitness landscape associated with a given task, genome/phenome and objective function is essentially constant, but population sizes can increase as a function of available computational power. Hence, a sufficiently large and diversified population with an appropriately set mutation rate might effectively smooth very rugged fitness landscapes, thus increasing the degree of complexity of tasks for which objective-driven evolutionary searches are tractable [18, 59].

D. Inadequate Theory and Issues of Human Cognition

In this subsection we take a more philosophical or theory-of-mind approach to our central question: if goal-driven ER methods could in fact support the automatic configuration of complex useful behavioral controllers, then why hasn't this been demonstrated? A possible answer to this question is that evolution of many complex behaviors might indeed have been attempted, but since negative results are rarely published in engineering-related fields (i.e. we attempted to design this system in this way and it did not work…), most such work would likely not have been published (except perhaps as part of a comparative study). Alternatively, such work may rarely have been attempted because skilled researchers often have a keen intuition related to which experiments might yield useful results. This might be considered a sort of *intuitive ceiling* in ER, and is potentially a liability in a field in which intuitions about processes and mechanisms are partially informed by artifactual aspects of human cognition. This subsection summarizes several of these possible artifactual aspects.

Human cognition, intuition and linguistic issues may play a significant role in introducing methodological and theoretical difficulties into the design of goal-driven artificial evolutionary systems [15, 16, 25, 74]. For example, [15] points out that there is little evidence or theory to connect evolutionary processes to increasing complexity, but that this concept remains a fixture in descriptions of natural selection. Furthermore, there seems to be an almost ineluctable propensity to conceptualize natural evolution's ability to generate self-replicators as a goal, rather than as an emergent property of an undirected process. This in turn leads to the idea that the perceived goal of self-replication (or at least replication efficiency) can be supplanted by some other goal or competency. However, outside a limited view of local adaptation, such views are inconsistent with modern theories of evolution as a fundamentally goalless process.

In a different vein, features of human cognition may allow researchers to mistake an agent driven by an essentially trivial algorithmic control mechanism for something displaying complex autonomous behavior. An example familiar to most autonomous systems researchers is illustrated by Grey Walter's tortoises or some of Braitenberg's vehicle experiments [75, 76]. Although these both seem to generate a degree of complex autonomous behavior, the algorithms used do not rise to the level of what might be considered minimal cognition. Pattee [25] touches upon this issue in the following quote: "This means that <artificial evolution> must evaluate its models by the strength of its theories… and not by technological mimicry alone. The high quality of computer simulations and graphics displays can provide a new form of artificial empiricism to test theories more efficiently, but this same quality also creates illusions." Considering that these words were written in 1987, before the rise of ER, the evolutionary robotics community should really take them to heart.

VI. The Current State of ER

In this final section, we discuss recent results as well as current efforts to overcome some of the problems and issues facing ER that were raised in this paper. The most promising methods to address goal-driven optimization's inability to drive evolution of complex information-intensive behaviors involve promoting rapid and extensive neutral drift in genome and/or behavioral spaces. Several such methodological changes to ER that might increase the degree of achievable complexity of evolvable behaviors are discussed. In particular, diversity maintenance methods that do not use task-specific information have been shown to increase the difficulty of tasks for which goal-driven selection is effective. Although these improvements would not fully generalize goal-driven artificial evolution, they may provide for at least an order of magnitude increase in behavioral complexity.

A. Complex Evolved Behaviors

In recent years some more complex evolved behaviors/tasks have been reported [2, 30, 32, 33, 56, 57, 59-62]. We highlight several of these to provide a context for a discussion of how current research reflects on the hypothesis presented in this paper.

In [57] a very complex version of phototaxis is studied. Robots are situated in an arena containing a light source which is surrounded by a circle drawn on the floor. If the circle has a break in it, the robots must approach the light via the break but may not cross the unbroken part of the circle. If there is no break in the circle, the robots must move away from the light. The work also includes an aspect of communication: robots are rewarded for producing a signal if they recognize that the circle is unbroken. This may help the other robots move away from the light without circumnavigating it, and this behavior was indeed observed in some evolved controllers. Controllers in only 3 of 10 evolutions were able to perform the discrimination task, and this may add weight to the view that fitness landscapes can become dominated by zero-plateaus as task difficulty/complexity increases.

Capi and Doya [56] report the evolution of a complicated sequential task in which a robot must visit three target/object locations repeatedly in a specific order. The robot relies on color vision to distinguish between the objects. The evolved controller was tested on a real robot. This work used a fitness function that was nearly free of task solution features, providing fitness feedback based on how many of the objects were collected in the correct sequence.

In [60] a group foraging task involving role allocation was evolved. Robot controllers were homogeneous, consisting of multi-layer recurrent ANNs. Some robots were required to remain within a color-demarked zone while others traveled to particular foraging sites and back to the demarked zone. The fitness function was tailored to a degree, but largely based on bootstrap elements and success rates at completing the two role-related tasks. Using homogeneous controllers makes this a very complex task.

Nitschke et al. [59] describe the evolution of many heterogeneous controllers for 30 or more robots in a sequential multiple-object foraging task similar to that described in [77]. In this work robots respond to various signals to find and deliver objects of several different types to a region in the center of an arena (some of which require multiple robots to transfer). This task is among the most complex reported in the ER literature and also used a more or less aggregate fitness measure based on the number of objects delivered in the right sequence. Although the task studied is of considerable interest, [77] and [59] demonstrated that a similar task could be accomplished with hand-coded locally reactive rules operating on the robots.

In [61] the authors employ an environmentally embedded fitness function based on "energy" collected and expended. Fitness is based only on energy levels of the robots, hence the task is implicitly to maximize energy collection, as per a foraging task. The robots must evolve to negotiate all aspects of their environment, and there is an implicit element of intra-population competition for the energy. One hundred simulated robots were used in initial phases of the experiment, and a simplified version was conducted using 20 real differential drive robots. This is a rarely implemented and robust method of increasing diversity and delaying convergence harkening back to Watson [31] and Werner [39].

In [32, 33] the use of hierarchical decomposition methods to combine evolved controller modules to accomplish complex tasks is investigated. In particular, the authors report on a very complex multi-robot object moving task in which three robots must locate an object in one room, move it to a door which must be opened by touching a target near the door, then move the object down a corridor and into another room. The authors decompose this task into six subtasks (five of which are evolved ANNs) and combine these with a high-level evolved controller (also a recurrent ANN). Although the authors don't prove that their task could not have been evolved without shaping, incremental or manual decomposition methods, they do highlight just how difficult such an endeavor would be.

In terms of complexity of evolvable behaviors, how do controllers generated using current ER methods (such as those reviewed above) compare to fully autonomous robot controllers developed using other more general methods? In order to judge this, let's look at a typical state-of-the-art example from the general field of fully autonomous systems for comparison. Because of the great diversity of research in ER and research in the larger field of autonomous systems, it is not practical to define exacting bounds on the whole range of possible autonomous behaviors. Current state-of-the-art fully autonomous systems are described in [81 - 83]. To pick one of these, [81] describes a robot capable of very sophisticated fully autonomous urban path planning and navigation. Here, the robot is given an arbitrary destination. In response, the robot makes use of an online map application to plan a course and then follow that course to the requested location. With very extensive decomposition, ER methods would likely be able to generate at least some of the component behaviors needed for this task, but high-level goal-driven evolution using aggregate selection could not be expected to drive the evolution of this competency. The point here isn't to put ER to an unfair test, but rather to highlight that simple goal-driven artificial evolution is quite limited, when viewed in the context of complex tasks involving a high degree of context-relevant information manipulation. With task decomposition and other augmentations, aspects of ER still provide utility, however this utility tends toward optimization as tasks become more complex, so that the goal of general automatic controller generation for sophisticated tasks is not feasible using artificial evolution driven by high-level task description alone.

B. State of the Art Methods in ER

We have touched on many of the current areas of ER research. In this subsection we bring these together and summarize them as a group.

Diversity maintenance methods are a potentially promising area of ER research. Novelty search [27, 28] uses measures of behavioral diversity to drive evolution, while other diversity maintenance methods are implemented with goal-directed fitness terms in weighted sums or via the use of multiobjective optimization methods [2].

In novelty search involving a decomposition of the robot-environment system into a behavioral description, a transform of the problem into a much more tractable domain is achieved [8] (as discussed in Section V.A). The main concern with these methods is that measuring diversity is an open problem, and it is possible that for complex problems, a fairly deep understanding of the solution space is needed [27, 78]. Novelty search methods have been used without explicit task oriented fitness functions [8]. It seems contradictory to fully renounce objectives in ER, and in some ways, one cannot expect to find a solution to a very specific, very complicated problem without at least an implicit selective bias. However, and perhaps counter-intuitively, if the evolutionary agent/environment is sophisticated enough, it might in fact contain solutions that while not being exactly fitted to a given arbitrary complex task, are within striking distance. Hence, as implied in [8, 28], an explicit objective can be implicitly sought in an environment in which a diverse population is engaged in open-ended evolution.

In the case of non-task-specific diversity measures such as those studied in [2] (summarize in Section V), the effect seems to be to increase the range over which goal-driven searches are effective. These methods are not fully characterized in the literature and may lead to a substantial increase in the achievable limits of goal-driven evolutionary search. Gains in performance due to diversity and novelty search enhancements, though, may ultimately be equivalent to those that might be achieved by using very large population sizes as in [59], asynchronous local reproduction [31, 39], environmentally embedded implicit fitness functions and very extensive training environments [61]. Our conclusion, though, is that diversity maintenance methods address problems of fitness landscape smoothing and population spread, but do not fully address the question of how to use artificial evolution for specific tasks of arbitrary complexity.

Some selection methods can provide progressive or continual selective pressure starting from completely random initial populations to populations capable of near optimal performance of a given task. Most complex fitness functions and incremental methods are intentionally designed to do this, that is, to guide the search through the solution space to a fit solution.

Simple aggregate success/fail fitness functions can also be formulated to provide progressive detectable selective pressure throughout the course of evolution when combined with competition in some special cases. This can be achieved in systems in which homogeneous or heterogeneous populations compete to perform a task that has both trivial and sophisticated solutions. This case is best exemplified by the evolution of game-playing neural networks for games such as Checkers and Go [79, 80]. Here, some percentage of games will come to an end with a winner, even if the opponents are abjectly incompetent and make nearly random moves. This allows a single progressive aggregate fitness function based only on number of wins in a tournament to be used to drive selection. This concept has received some attention in ER in relation to evolving populations of controllers for competitive behaviors [10, 23].

VII. Conclusion

In terms of complexity of behaviors and using current state of the art ER methods, the limits of relatively non-biased goal-driven artificial evolution appear to be in the range of the complexities of tasks such as those reported in [33, 60]. In light of the very considerable amount of research reported in ER over the last 25 years, and the lack of any fully evolved autonomous robotic system that might approach the state-of-the-art performance of autonomous systems in general [81-83], it is likely that some methodological aspirations of ER are not feasible using current or near future technology. This paper has presented several arguments suggesting that direct goal-driven evolution of very complex autonomous robot behaviors, although possible in some specific cases, is not tractable in the general case.

Topology smoothing and GA enhancement methods, including task-independent diversity maintenance and environmentally situated asynchronous GAs, are not yet fully characterized in the literature and may lead to significant improvements in ER. Recently, more generalized methods involving design and engineering combined with a more optimization-oriented use of artificial evolution have been shown to out-perform pure evolutionary approaches. These incremental approaches may indeed represent the future of ER for some time to come.

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