AutoFac: The Perpetual Robot Machine

Geoff Nitschke, *Member, IEEE*, David Howard, *Member, IEEE*

***Abstract*—Robotics currently lacks fully autonomous capabilities, especially where task knowledge is incomplete and optimal robotic solutions cannot be pre-engineered. The intersection of *evolutionary robotics*, *artificial life* and *embodied artificial intelligence* presents a promising paradigm for generating multi-task problem-solvers suitable for adapting over extended periods in unexplored, remote and hazardous environments. To address the automation of evolving robotic systems, we propose fully autonomous, embodied artificial-life factories and laboratories, situated in various environments as multi-task problem-solvers. Such integrated factories and laboratories would be adaptive solution designers, producing fit-for-purpose physical robots with accelerated artificial evolution that experiment to continually discover new tasks. Such tasks would be *stepping-stones* towards accomplishing given mission objectives over extended periods (days to decades). Rather than being purely speculative, pre-requisite technologies to realize such factories have been experimentally demonstrated. Currently, vast scientific and enterprise opportunities await in applications such as asteroid mining, terraforming, space and deep sea exploration, though no suitable solution exists. The proposed embodied artificial-life factories and laboratories, termed: *AutoFac*, use robot production equipment run by artificial evolution controllers to collect and synthesize environmental information (from robotic sensory systems). Such information is merged with current needs and mission objectives to create new robot embodiment and task definitions that are environmentally adapted and balance task-oriented behavior with exploration. AutoFac is thus generalist (deployable in many environments) but continually produces specialist solutions within such environments — a perpetual robot machine.**

***Impact Statement*—With recent advancements in robotics material science, evolutionary machine learning and rapid prototyping technologies, such as 3D and 4D printing, the notion of self-adapting, self-replicating and self-sustaining robot-colonies is closer to reality. Automatically produced robot-colonies would be akin to their biological counterparts — *body-brain designs* adapted to specific environments. Such automation would be directed by high-level user-assigned tasks augmenting traditional notions of survival in nature, to provide a focus for perpetual adaptation (evolution). Central to such robot-colony automation is the notion of a *smart factory*, continually balancing resources, recycling materials, and designing robots specifically suited to their environments. This will enable continuous operation without human intervention in remote, hazardous and inhospitable environments such as other planetary bodies and the deep-sea.**

***Index Terms*—Autonomous Systems, Collective Behavior, Evolutionary Computation, Robotic Assembly, Automatic Generation Control, Manufacturing Automation.**

AutoFac: The Perpetual Robot Machine: Submitted for review in 2020. This research is supported by the *Commonwealth Scientific and Industrial Research Organisation* (CSIRO) Distinguished Visiting Researcher competitive funding program and South African *National Research Foundation* (NRF) Human and Social Dynamics in Development grant (Grant No: 118557).

Geoff Nitschke is with the Computer Science Department, University of Cape Town, South Africa (e-mail: gnitschke@cs.uct.ac.za). David Howard is with CSIRO, QCAT, 1 Technology Court, Pullenvale, 4069, Australia (e-mail: David.Howard@csiro.au).

I. INTRODUCTION

THere is an increasing need to deploy robotic systems in unexplored, inaccessible, dynamic, remote and hazardous environments[1] where manual access (for example, for maintenance) is impractical [2], and a lack of environmental information means that optimal robotic form and function are impossible to pre-engineer. Despite amenability to automation, current robotic solutions cannot perform satisfactorily in such scenarios, whether mining asteroids, pre-installing off-world infrastructure for human habitation, or conducting extended scientific studies in the ocean depths. Successful deployments imply autonomy and self-support, frequently seen in nature, but missing from fabricated solutions. Such solutions would enable the realisation of untold benefits and applications.

In solving these problems, we may consider two common approaches. First, we produce a single *swiss-army-knife* robot; complex, with an array of different sensors, operating behaviors and the ability to morph itself into different configurations according to its role. Such a robot would require an intensive engineering effort, be expensive, and lack redundancy [3]. Second, one can conceive a swarm of biomimetic robots, with distributed control and designed from robust soft materials [4], yet still unable to replenish or recycle themselves into new and improved generations.

We focus on a third option, an autonomous, self-adapting robot factory and laboratory, capable of continually producing populations of effective and efficient task-adapted robots that continually explore, experiment with and refine solutions to immediate mission needs. We thus propose *AutoFac*, a hybrid of artificial embodied evolution [5], swarm robotics [6] and advanced manufacturing [7], [8] systems. AutoFac is a fully automated robot designer and fabricator and evolving collective behavior controller, that permits continued adaptation of robot body-brain designs, potentially over years, accounting for shifting objectives and environmental variations. AutoFac strategically allocates limited resources to persist in its environment, while also achieving given goals. We describe AutoFac's main properties and its timely inception given recent rapidly-emerging technologies that can be combined as autonomous self-sustaining robotic systems.

Perpetually adaptive and self-replicating robots, situated in new environments, are envisaged as embodied *multi-task* problem-solvers. One pertinent example is automated exploration [9] and terraforming [10] of other planetary bodies.

[1] "Space and ocean probably represent the most challenging environment for robotics. Both regimes push the limit of sensing, control, and manipulation of robotic systems with extremely harsh conditions." [1]

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TAI.2021.3104789, IEEE Transactions on Artificial Intelligence

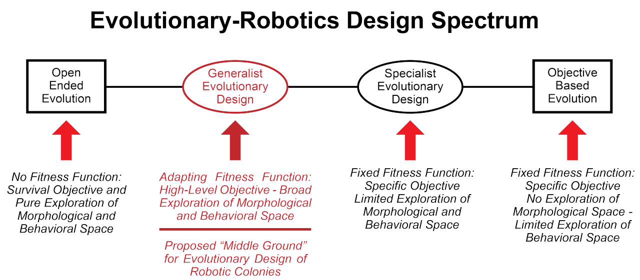

Fig. 1. Evolutionary-robotic design spectrum, ranging from open-ended evolution with no explicit fitness function (*far-left*) to fitness function driven behavioral evolution in fixed morphology robotic systems (*far-right*). AutoFac is conceptually at spectrum's *middle-ground* (highlighted in red), since as an embodied artificial-life factory, it adapts to given high-level objectives, and thus generates robotic organisms that adapt to their environment via progressive (evolutionary) exploration of the space of robot behavior-morphology designs. Note that this is closer to *open-ended evolutionary systems* [13], since *AutoFac* produced robot populations must continually evolve to survive in their environment (via adapting their bodies, brains and thus behaviors).

These are complex problems comprising a multitude of tasks that must be completed in order for exploration and terraforming missions to be successful. For example, given the complex engineering problem of low-cost autonomous colonisation of the Moon [11], [12], robots deployed would be required to solve a diverse range of inter-dependent tasks, including mechanical parts manufacture for machinery that enables mining and chemical processing (of *in situ* resources), before such a colonisation mission could be considered successful.

The AutoFac Vision

We envisage AutoFac as a *situated* and *embodied* problem-solver that automatically creates, *on-demand*, self-adapting and self-sustaining robotic artificial life communities. Such robotic colonies are to be deployable to any environment and adapt themselves to solve specific tasks and missions. AutoFac would ideally be deployed to remote, uninhabitable or hostile environments, to fulfil general mission objectives for which we currently do not have solutions. Specifically, where embodied systems must solve tasks over extended time-frames using adaptable, robust collective behavior, robot body-brain specializations as prerequisites to given mission (problem-solving) success. Prospective deployments include environmental cleanup [14], disaster management [15], asteroid mining [16] and space exploration [17].

We position *AutoFac* as *middle-ground* on an evolutionary robotic design spectrum (*center-left*, figure 1). This spectrum middle-ground encapsulates situated and embodied, self-sustaining, artificial life systems that continually adapt to their environment while addressing a high-level objective. For example, *survival* in artificial life systems and in the case of AutoFac, user-defined *mission* objectives such as geological resource discovery, terraforming and mining. At the spectrum's far-left (figure 1), we classify robot evolutionary design under *open-ended evolution*, where the artificial evolution is not driven by fitness functions, but rather just robot survival and propagation [13]. At the *far-right* of the spectrum, robot evolution is directed by fitness functions so as robots adapt to solve specific tasks in specific environments. In embodied systems, robot morphology is fixed and controllers (behaviors) are evolved (for example, using neuro-evolution [18]), over the course of robot lifetime, or otherwise adapted for given simulated tasks and subsequently transferred to physical robots [19]. The spectrum *center-right* classifies embodied evolutionary robotics research where behavioral adaptation to morphological change occurs within a robot's lifetime. Such research assumes a mutable physical robot substrate from which various robotic designs can be self-assembled. For example, the proposed *smarticle* system [20], could form the basis for robotic self-assembly and emergent control of task-capable ensemble machines [21].

Our vision for *AutoFac* is as harmonious integration of an autonomous, situated and embodied artificial life (robot) *factory* and *laboratory*. As an autonomous robotic factory, AutoFac runs *on-demand* robot body-brain design and manufacturing. As an autonomous laboratory [22], AutoFac formulates and executes to experiments using physical robots [23], to enable scientific discovery and exploration as *stepping-stones* [24], [25] towards accomplishing given objectives. *AutoFac* would be best suited to environments where we currently do not have optimal, working solutions to many societal challenges. For example, in deep-sea or extraterrestrial [1] environments, where specific objectives must be completed, but how to do so is unknown and first requires some process of environment exploration and scientific discovery [2].

II. AutoFac: Proposed Functionality

AutoFac's proposed functionality is autonomous laboratory and self-sustaining robot factory (figure 2). AutoFac is proposed to be a multi-task problem-solver, so when situated in a given environment and assigned a complex problem (comprising multiple tasks), automatically designs suitable problem-specific experiments, executable by automatically designed and produced robots, deployed in the environment. Via testing and evaluating such experiments, the robots enable environment exploration, scientific discovery and contribute potential solutions towards solving complex user-defined problems. We envisage future scenarios where AutoFac will automate design and production of robot populations that operate in extreme environments (usually inhabited by only *extremophile* organisms [26]), for user-defined missions such as planetary terraforming [27], asteroid mining [28], deep-sea exploration [29], and autonomous farming [30].

AutoFac's process of environment observation, experiment and robot design, physical robot production for environment monitoring and experiment evaluation, continues *ad infinitum*. Though, as given problems are solved, new problems could be assigned, meaning AutoFac can operate in perpetuity to produce robots adapted to exploration, scientific discovery and problem solving. This proposed functionality is enabled by recent technological and scientific advances in evolutionary

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TAI.2021.3104789, IEEE Transactions on Artificial Intelligence

robotics, rapid-prototyping, and material science under the themes of *collective behavior*, *morphological computation* and *embodied evolution* research (figure 2: *base*, section III: *AutoFac technological basis*). AutoFac's key functionality is *adaptive persistence*, to balance survival (robot adaptation) and exploration (data-gathering and scientific discovery for selecting tasks to solve towards user-defined objectives).

AutoFac would be deployed in novel, unexplored, remote or otherwise hazardous environment with an initial resource-base of materials for robot manufacture. Initial environment sensory observation would enable artificial evolution simulation (enriched by sensor data) to evolve and manufacture initial physical robot designs, deployed into the environment to explore and discover task objectives contributing to solving an overall user-defined mission objective. Embodied evolution would be used to recombine, reuse and recycle current robots to perpetuate future generations of improved *body-brain* designs that continually satisfy changing task objectives.

As an *autonomous factory*, AutoFac designs and constructs robotic explorers deployed into any environment, where as an *autonomous laboratory*, AutoFac discovers various tasks (as *stepping-stones* [24], [25] to a given objective), that robot behavior evolves to accomplish. Data gathered by populations of robotic explorers, *(i)* updates the simulator, allowing progressively better robot-environment couplings, which in turn improves task performance, and *(ii)* increases situational awareness, revealing pertinent resources (for example, to be gathered and returned to AutoFac's *base* and *factory*).

We envisage the main controller cycles of AutoFac as: *robot lifetime* and *data collection*, where the efficacy of robotic designs (operating concurrently in overlapping lifetimes as in biological communities), is iteratively improved via new sensor data gotten from exploration and resources in dynamic environments (figure 2: *top*). AutoFac will operate on a time-scale of many years, meaning seasonal weather patterns and environmental change will play a critical role in robotic adaptation produced via embodied evolution. This entails AutoFac producing robot generations (running for given *lifetimes*) via processing, recycling and reusing materials [31], where such robots comprise improved body-brain designs that solve increasingly complex tasks. Concurrently, AutoFac gathers and processes sensory information from physical and behavioral challenges encountered as robots explore the environment. Such *data collection* is indispensable for evaluating task performance, identifying *stepping-stones* [24], [25], shaping fitness functions and enabling exploration [32].

In summary, AutoFac serves first as an autonomous factory, automating the design and production of successive generations of robot populations, specially suited to accomplishing tasks that contribute to an overall mission objective. Second, AutoFac is as robot scientist [33] or autonomous laboratory [34], that automatically derives hypotheses to explain observations, devises experiments to test these hypotheses and physically runs experiments an

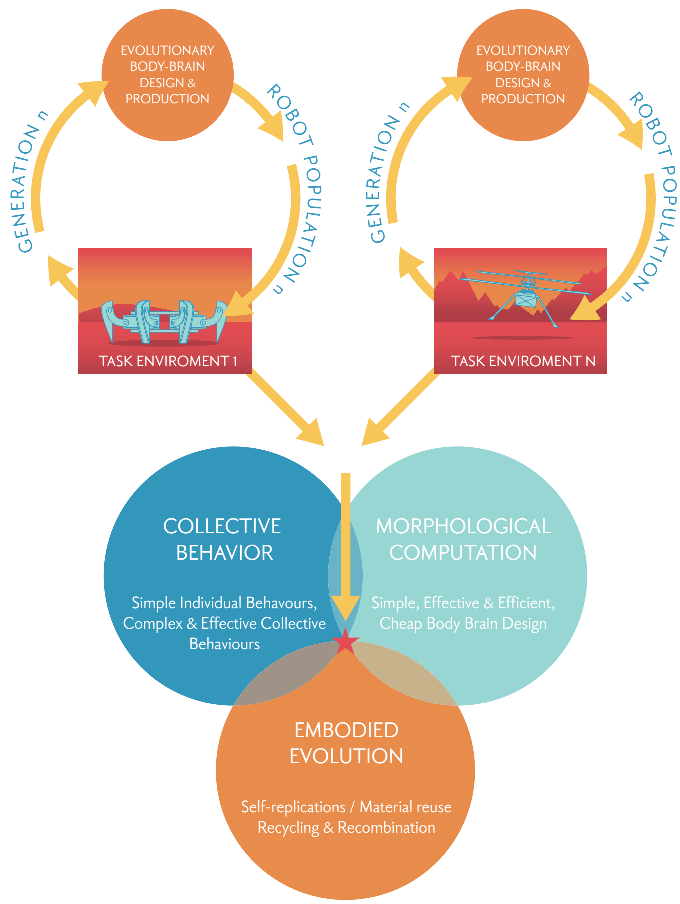

Fig. 2. AutoFac is an embodied artificial life factory leveraging benefits of *collective behavior* and *morphological computation* to enable *embodied evolution* of consistently improving populations of simple and yet effective robots. AutoFac is an autonomous factory and laboratory that designs robotic solutions for tasks in various environments. For any given task environment: (1. . .N), *AutoFac* artificially evolves, over generations of physically produced robots, body-brain couplings that adapt to the robots' environment and solve specific tasks that contribute towards solving a complex user-assigned mission.

experimental situated and embodied platform enabling robots to interact with their environment over extended periods.

Continuing cycles of such experimentation for scientific discovery suitably complement the cycle of evolutionary robot design and production, in that each robot population (generation) effectively constitutes the experimental-conduct tools [23]. Such experimentation is critical for AutoFac to meaningfully process sensory environment data gathered from the robot population and thus deduce what the next task should be and how to best accomplish the task, where each task constitutes a *stepping-stone* towards overall task (mission) accomplishment.

III. AutoFac Methodology: Technological Basis

Conventional robots execute pre-defined tasks using specially programmable procedures in controlled and structured environments. Next generation robots will operate in unconstrained dynamic environments under the general direction of human operators. One step further, robots produced by AutoFac must work in remote, hazardous environments as fully exploratory and adaptive autonomous systems that potentially

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TAI.2021.3104789, IEEE Transactions on Artificial Intelligence

operate as robot colonies adapted for long periods of scientific discovery or commercial enterprise. In such scenarios, manufactured robots must correctly perceive the external world and adapt their behavior accordingly. Here we overview recent technologies pertinent to the core methodology of *AutoFac*.

A. Embodied Evolution:

Core to *AutoFac's* methodology is the evolutionary search for robotic (body-brain) designs, manufactured for given physical environments, evaluated as problem-solvers in these environments, and then re-used or recycled into the next generation of increasingly-adapted robots. Figure 2 (top), presents an *embodied evolution* example where *AutoFac* has manufactured robots (walking and flying) after n generations of body-brain evolution. Embodied evolution necessitates a robot body-brain evolutionary algorithm, fabricator and recycler (*autonomous factory*), and a sensory data-gathering system for fitness function discovery (*autonomous laboratory*). Robots would return to AutoFac *ad hoc* as tasks are completed and to have material components recycled and recombined for manufacturing next generation robots.

In figure 2, the generational cycles of evolving walker and flying robots are assumed asynchronous given varying terrain types and thus correspondingly suitable robot evolution. The AutoFac methodology borrows from *embodied evolutionary robotics* [35], but mimics *ad hoc* reproduction by organisms in nature, and thus best relates to *open-ended evolution* artificial life systems [13], where the need to survive in environments with limited resources drives adaptation. In the case of *AutoFac*, task discovery and specific robot body-brain designs as evolved problem-solving products act as *stepping-stones* towards accomplishing user-defined directives. Recent advances in *3D robot-printing* as part of embodied evolution [36], [37] and *4D printing* [8] (origami-robotics [38]), using multi-material (soft-robotics) and directed-assembly approaches (guided-self-organization [39]), have demonstrated potential to address this design-fabricate-test and recycle embodied evolution challenge. Such advances offer a new robotic design paradigm going beyond traditional mechatronics using gears and motors, to enable the automatic design of currently unforeseen robot forms and functionalities. However, significant advances are required to deliver robust traversal strategies, and hybridisation. That is, selective use of technologies would help to deliver usable solutions by mitigating drawbacks of each respective technology in isolation. For example, the relative fragility of origami designs may preclude uses involving direct environmental contact, but may be directly applied to the creation of components with no load bearing requirements).

We propose AutoFac's robot design paradigm as the rapid-prototyping and manufacturing of mechatronic and soft robotic hybrids using evolvable artificial active matter [40], [41]. That is, using flexible artificial skins [42], [43] and self-healing soft materials [44], [45], means soft-robots can perform tasks in uncertain, dynamic environments without extensive control systems. Given 3D and 4D printing advances, new material types such as *Shape Memory Materials* (SMMs) and *Shape Memory Polymer Actuators* (SMPAs) [46] are proposed for rapid-prototyping fabrication schemes to create material systems (robots) with multiple functions, such as actuation and self-healing [45]. This will necessitate integrating biological materials and biodegradable substrates [7] with 3D soft-robotics and 4D origami-robot printing (capable of self-assembling into pre-programmed shapes at scales from micrometers [47] to centimeters [48]). Also, the use of *smart* multi-responsive materials [7] will be crucial for the successful development of future robotic actuators in origami-robots printed with forms and functions specific to their task and environment. For example, integrating materials such as magnetic, light-responsive, micro- and nano-structures, to form 4D-printed composite components will present new opportunities in smart robotic actuators [8]. Consider that, in a population of AutoFac produced robotic explorers, environmental changes could be stimuli for body-brain adaptation, since smart-materials would allow robots to *self-fold* in response to external stimuli such as changes in light, temperature, and humidity [38]. Such an approach would meet the challenge of automated robot body-brain design for any given task and environment as part of AutoFac's embodied evolution (figure 2: *base*).

B. Collective Behavior:

Collective behavior [49] is the next critical methodological basis from which to draw technological components for the proposed *AutoFac* systems (figure 2: *base*). Collective behavior is decentralised with no centralised information processing center. In nature, collective problem solving behavior is often observed in social insects [50], [49]. One key notion of *AutoFac* is its embodied evolution process designs and produces robot populations eliciting problem-solving collective behaviors. AutoFac's autonomous *robot factory* and *laboratory* components (section I) in concert with robot populations constitute a collective behavior system, akin to ant colonies or bee hives [50], [49]. Thus, as in such biological collective behavior systems, collective problem-solving behaviors emerge from individual interactions, where the physical manifestation of *AutoFac's* embodied evolution (robot populations) is most pertinent to *collective* [51] and *swarm robotic* [6] systems. *AutoFac* would initially produce a random-sized robot population, though as in biological systems, population size necessarily fluctuates according to varying task and environment constraints and requirements.

Collective problem-solving behaviors emerge from *lifetime*[2] interactions, with benefits such as redundancy, concurrency [51], [6] and specialized form (morphology) and function (behavior) [52]. Figure 3 illustrates an example collective robotic behavior, produced for exploratory missions on other planets. Specialized robot form and function, concurrency and redundancy, is evolved for specific tasks and environments. For example, multiple robots (with crawling versus flying forms) are engaged in data-gathering over rugged versus flat

[2]Determined by task-solving time, duration of materials, components and power source, unexpected damage, or return to factory for recycling.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TAI.2021.3104789, IEEE Transactions on Artificial Intelligence

terrains, while dissimilar robots engage in complementary tasks such as geological analysis (*robot working*, figure 3).

Various embodied collective and swarm robotic systems have been demonstrated as autonomous and adaptive collective behavior systems [53], [54], [55]. For example, automated decentralized collective construction[3] by cooperating robots, built *on-the-fly* given site-specific environmental conditions and constraints [57], [54], [58], [59]. Pertinently, we envisage *AutoFac* designed and produced robot populations as capable of exhibiting a broad range of collective behaviors. Potential collective construction manifestations include construction of novel, customized and dynamic functional structures (equipment) that contributes to task discovery, fitness function shaping [32] and thus overall mission accomplishment. For example, constructed equipment such as multi-modal sensors for on-site environmental data collection, actuators for local material excavation or chargeable batteries using specialized actuators such as deployable roll-out *photovoltaics* [58].

Though in *AutoFac*, or any artificial (robotic) collective behavior system, collective behavior efficacy strongly depends on the behavior-morphology design of individual robots and their interactions [60]. While conceptual and methodological groundwork, such as *self-organization* [54], [55] and *self-assembly* [53], for designing collective behavior has already been demonstrated, the embodied evolutionary design [60] of specialized robot forms and functions will enable a vast range of collective behaviors and problem types to be solved by AutoFac produced collective and swarm robotic systems. Such broad collective problem-solving behavior will be further enabled by *4D printing* [38], and related work in *guided self-organization* [61] and *morpho-genetic engineering* [62], for increased adaptation and malleability of functional robotic structures. Such approaches, in concert with embodied evolution, will enable the design and production of robotic swarms with highly adaptable forms and functions that readily change in response to task and environment changes. Individual robot adaptations thus determined the problem-solving effectiveness of robot populations.

For example, morpho-genetic engineering has been applied for self-organization of organic and adaptable shapes in swarm-robotic systems, making them robust to damage [63]. In AutoFac, morpho-genetic emergence of highly functional robotic forms could potentially solve a myriad of collective behavior tasks in unpredictable and unexplored environments. This includes, self-organizing swarms into complex machines (for example, satellites) to act as environmental monitoring, mapping, communication or other devices [64].

Guided-Self Organisation (GSO) [65], [66] research has indicated potential for adaptive, self-organising, artificial collective behavior systems extracting local interaction mechanisms from robot sensory data, enabling emergent and adaptive individual and collective behavior. GSO [61] is the manipulation of complex-system nodes and interactions so as new system-wide behaviors emerge, guiding the system towards desired states. This implies computational GSO methods adapt node behavior and interactions in artificial collective behavior systems (for example, AutoFac designed and produced robot populations) such that the system self-regulates, and appropriate global behaviors emerge in response to external (for example, user defined goals) and internal system changes (for example, unexpected damage). We hypothesize hybridizing computational GSO with various evolutionary and behavioral [67], [68] adaptation approaches, including developmental body-brain encoding [69], [19], will enable emergent collective problem-solving behaviors for many tasks [70].

[3]In decentralised collective construction, structure design is an emergent property as observed in wasp and termite mound construction [56].

C. Morphological Computation:

A key *AutoFac* technological component (figure 2: *base*), is *morphological computation* [71], [72]. Practical limitations of embodied evolution [73], [35], [36], [37], constrained by limited sensor, actuator and material resources for manufacturing necessitate robotic body-brain design emphasising minimalism and efficiency. That is, where suitable use of materials and components means robot morphology can elicit desirable behavior that belies the apparent simplicity of the design. *Morphological computation* enables task-specific body-brain design simplicity, though open-ended robotic embodied evolution that fully leverages the benefits of morphological computation to produce specially task-suited robots with efficient and minimalist designs remains a frontier topic [74].

In embodied evolution and physical robot manufacture, new material types, including those recycled and recombined into new materials and components, will play an integral role in AutoFac leveraging morphological computation during robot body-brain design. Recent developments of multi-material 3D printing technologies have accelerated new material use in robotics [75], allowing digital fabrication of heterogeneous structures with tailored mechanical, electrical, and optical properties. Ideally, this will facilitate the printing of morphological structures where significant computation is off-loaded to, or distributed throughout, robot material composition.

D. AI Methodologies and Techniques:

We now describe the core AI algorithms, architectures, and emerging technologies to realize key capabilities of AutoFac.

Adaptability and resilience can be engendered through the development of contemporary learning approaches. In particular, those that adapt behavior over long time frames, including *reinforcement learning* [76] in individual and group-based contexts [77]. Software-based damage adaptation is required as sensor and actuator damage from unexpected task and environment challenges will be common - approaches include maintaining a diverse library of tuned behaviors, and use of on-board physics simulation paired with data-driven

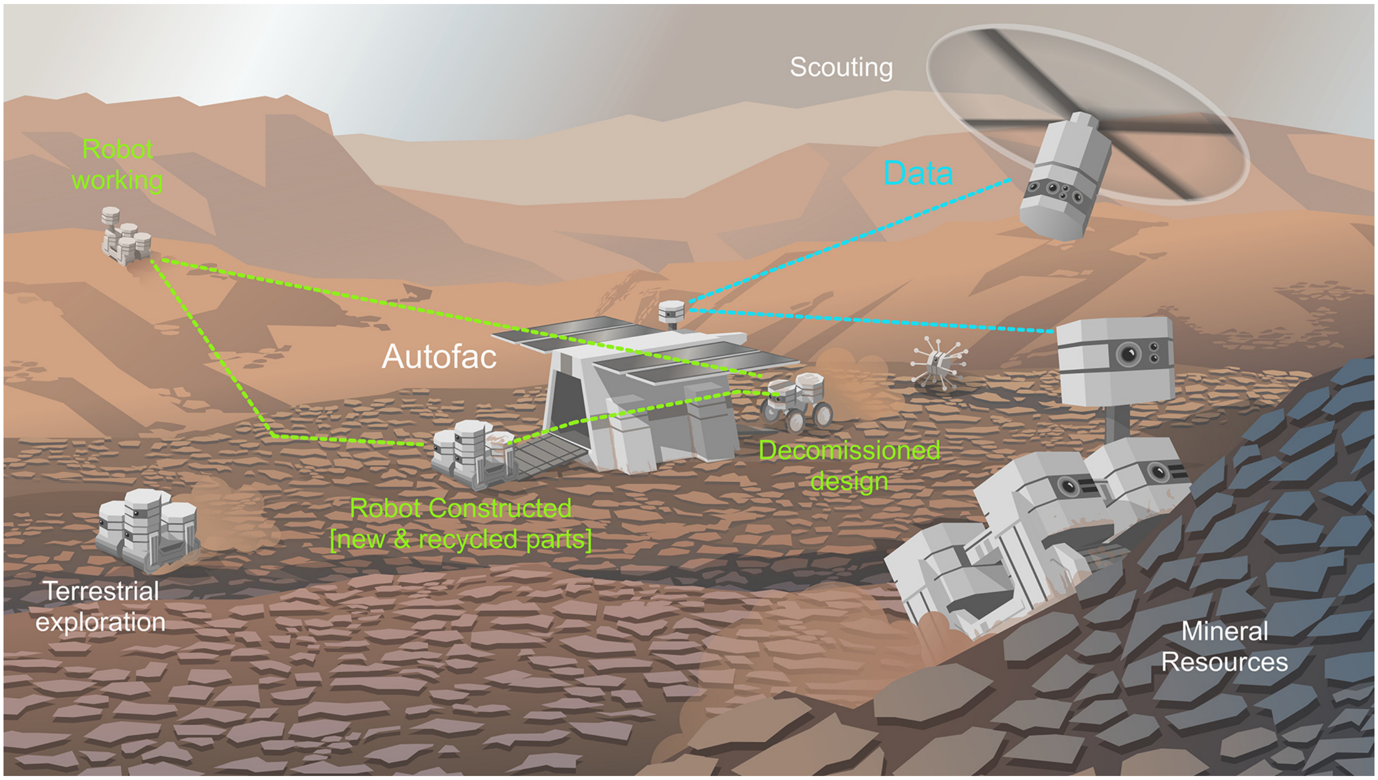

Fig. 3. An artist's rendition of an *AutoFac* system deployed on another planetary surface and given user specified mission goals to gather scientific data. AutoFac automatically designs and produces robots suited to the task. As various challenging task and environmental conditions are encountered, such as canyons and mountains, data pertinent to robot controller-morphology design and problem-solving is streamed back as initial robots return to AutoFac. Composite robotic component materials are then recycled and recombined for design and manufacture of new robots. Such new designs continue exploration of the environment gathering data that AutoFac concurrently processes for continued embodied robotic controller-morphology evolution.

adaptation to real-world conditions [78], [68], [79], [80], [81].

Self-directed learning is required for exploration and exploitation of unknown environments. Self-supervision [82] allows AutoFac to derive its own reward signals from the environment, and techniques including artificial curiosity [83] permit goal-oriented behaviors in the absence of strong reward signals. Semi-supervision reduces the requirement for labelled data and has been previously applied in a robotics context [84]. To improve robot utility (important considering the limited array of modules that will be initially available), multi-task learning [85] is key to flexible and adaptable robot populations that can effectively role-switch. Simulation [86] is required for fast, cheap, parallel implementation of these learning algorithms. Crossing the *reality gap* [87] allows these algorithms to be deployed in reality. Curriculum learning [88] allows gap-crossing as well as the incremental learning of locomotion strategies over increasingly complex terrains [89]. Extracted *stepping-stone* features can be automatically mapped into new fitness functions [24].

Collective adaptive behavior is a machine learning ensemble [90] for distributed decision making and problem solving. Recent DARPA[4] challenges focusing on robotic teams demonstrate several key technologies, for example, multi-robot task allocation, dynamic mission planning, and joint situational awareness through a shared global understanding of the environment [91] and required tasks using heterogeneous robots [92]. Fleet learning [93] can provide distributed knowledge transfer and model updates across the team. An end goal is AutoFac as a distributed robotic embodiment of *autonomous experimentation* [22]. This nascent field (in robotics) is based on model-building from collected real-world data points, and subsequent use of models to predict high-value future experiments. Experiments may be focused on accomplishing mission goals, exploration of AutoFac's local environment, and of the possibilities afforded by its modular robot morphologies to solve tasks.

Autonomous robot design provides the physical manifestation of AutoFac's problem-solving capability. Straightforwardly, modular robotics [94] provides early solutions for planning, control, and synchronisation, and techniques including graph grammars [95] can assemble the modules into high-performance robots. Further design freedom is achievable via automatically-defined modules (for example, limbs) [96] that can be easily 3D printed, and subsequently automatically assembled into finished artefacts [97] with specific consideration of the manufacturability of the robots [98]. Simulation can be tuned to reality by injection of real-world data such that "the complexity of virtual robot designs does not outpace the model limitations or available fabrication technologies" [99]. Individual robots may also adapt morphologically on-line

[4]Defense Advanced Research Projects Agency

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TAI.2021.3104789, IEEE Transactions on Artificial Intelligence

through re-configurable hardware, increasing the diversity and flexibility of modular building-blocks [100].

E. Hardware

Ongoing developments in hardware play an important role in the realisation of AutoFac, particularly in multi-functional materials that couple sensing, actuation, computation, and communication [101], and printable batteries [102], circuits, and sensors [103] to realise a flexible array of customisable embodiment options. It is anticipated that artificial active materials used in robot production will carry out basic computation and adaption without referring to *in silico* (machine learning) training procedures, via incorporating signal inputs, signal processing and memory storage into microscopic materials [39]. Heightened levels of material computation are more amenable to controller coupling in an embodied cognition framework [75]. Re-use is inherent in modular robotics setups, however in other cases recycling [104] may be required to keep material stocks high. Implementing learning algorithms in hardware offers significant opportunity for high-speed, low power control for long-term deployments [105], particularly for neural approaches that can also realise short and long term plasticity, and hence flexible learning [106], [107].

Why AutoFac and Why Now?

Fully automated, self-sustaining embodied robot evolution *factories* and *laboratories*, deployable to any environment, elicit many benefits. A compelling motivation is for user objectives, scientific discovery (problem-solving *what to do*), then design and production of robotic solutions (problem-solving *how to do it*) for any given environment, is fully automated. Fully automated robot design and continued robot body-brain adaptation, potentially over years using *in situ* resources, would be an indispensable design and problem solving tool for future robotic missions, presenting a unified research pathway that, if successful, would solve a number of current robotics grand challenges [108]. For example, figure 3 presents the decommissioning (recycling of materials and components) of previous generation robots into next generation robots with new forms and functions, suitable for solving newly discovered tasks. Here, a previous generation exploratory rover has been decommissioned and recycled into a next generation robot specialized to geological analysis (*robot working* in figure 3). Biomimetically inspired robots [109], [110], artificially evolved and autonomously manufactured [7], [8] in their given environments are proposed as future solutions over pre-engineered robotic systems [111], given grand challenging objectives. That is, objectives such as environmental cleanup [14], disaster management [15], space exploration [17], search and rescue [112] and asteroid mining [16], have high societal value and many are current *grand challenges* in robotics [108].

If we are going to solve the greatest challenges facing humanity in this century, then we will need automated, perpetually adapting, embodied systems that operate in changing environments, deriving novel solutions to arduous problems (that human designers could not otherwise design). Automating this problem-solving will be via virtue of automated embodied systems (*AutoFacs*) evolving embodied machines with novel *forms* (bodies) and coupled *functions* (controllers). Grand challenges that these automated self-designing embodied problem-solvers would be pitched at include, optimal low-cost automated farming in adverse environments and food production to satisfy ever-increasing global demand, swiftly deployable automated disaster management for increasing climate related catastrophes, and automated scientific exploration and discovery of alternate energy resources to reduce global reliance on environmentally damaging fossil fuels.

References

[1] N. Jacobstein, J. Bellingham, and G.-Z. Yang, "Robotics for Space and Marine Sciences," *Science Robotics*, vol. 2, no. 1, 2017.
[2] J. Bellingham and K. Rajan, "Robotics in Remote and Hostile Environments," *Science*, vol. 318, no. 5853, pp. 1098–1102, 2007.
[3] W. Tan, H. Wei, and B. Yang, "SambotII: A New Self-Assembly Modular Robot Platform Based on Sambot," *Applied Sciences*, vol. 8, no. 1719, 2018.
[4] Y. Wu and et al., "Insect-Scale Fast Moving and Ultrarobust Soft Robot," *Science Robotics*, vol. 4, no. 1, 2019.
[5] A. Eiben and J. Smith, "From Evolutionary Computation to the Evolution of Things," *Nature*, vol. 521, no. 1, pp. 476–482, 2015.
[6] M. Schranz, M. Umlauft, M. Sende, and W. Elmenreich, "Swarm Robotic Behaviors and Current Applications," *Frontiers in Robotics and AI*, vol. 7, no. 36, 2020.
[7] P. Fischer, B. Nelson, and G. Yang, "New Materials for Next-Generation Robots," *Science Robotics*, vol. 3, no. 1, 2018.
[8] C. de Marco, S. Pane, and B. Nelson, "4D Printing and Robotics," *Science Robotics*, vol. 3, no. 1, 2018.
[9] S. Chien and K. Wagstaff, "Robotic Space Exploration Agents," *Science Robotics*, vol. 2, no. 1, 2017.
[10] E. Vaz and E. Penfound, "Mars Terraforming: A Geographic Information Systems Framework," *Life Sciences in Space Research*, vol. 24, no. 1, pp. 50–63, 2020.
[11] A. Ellery, "The machine to End all Machines — Towards Self-replicating Machines on the Moon," in *Proceedings of the 2018 IEEE Aerospace Conference*. doi: 10.1109/AERO.2018.8396378: IEEE Press, 2018, pp. 1–17.
[12] ——, "How to Build a Biological Machine Using Engineering Materials and Methods," *Biomimetics*, vol. 5, no. 35, p. doi:10.3390/biomimetics5030035, 2020.
[13] N. Packard and et al., "Open-Ended Evolution and Open-Endedness," *Artificial Life*, vol. 25, no. 1, pp. 1–3, 2019.
[14] B. Bayat and et al., "Environmental Monitoring using Autonomous Vehicles: A Survey of Recent Searching Techniques," *Current Opinion in Biotechnology*, vol. 45, no. 1, pp. 76–84, 2017.
[15] V. Jorge and et al., "A Survey on Unmanned Surface Vehicles for Disaster Robotics: Main Challenges and Directions," *Sensors*, vol. 19, no. 3, pp. 1–10, 2019.
[16] J. Lewis, *Mining the Sky: Untold Riches from the Asteroids, Comets, and Planets*. New York, USA: Perseus Publishing, 1997.
[17] M. Sabatini and G. Palmerini, "Collective Control of Spacecraft Swarms for Space Exploration," *Celestial Mechanics and Dynamical Astronomy*, vol. 105, no. 1, pp. 229–244, 2009.
[18] K. Stanley, J. Clune, J. Lehman, and R. Miikkulainen, "Designing Neural Networks through Neuroevolution," *Nature Machine Intelligence*, vol. 1, no. 1, pp. 24–35, 2019.
[19] F. Silva and et al., "Open Issues in Evolutionary Robotics," *Evolutionary Computation*, vol. 24, no. 2, pp. 205–236, 2016.
[20] W. Savoie and et al., "A Robot made of Robots: Emergent Transport and Control of a Smarticle Ensemble," *Science Robotics*, vol. 4, no. 1, 2019.
[21] S. Batra and et al., "Particle Robotics based on Statistical Mechanics of Loosely Coupled Components," *Nature*, vol. 567, no. 1, pp. 361–365, 2019.
[22] R. King and et al., "The Automation of Science," *Science*, vol. 324, no. 1, pp. 85–88, 2009.
[23] S. Stanton, "Situated Experimental Agents for Scientific Discovery," *Science Robotics*, vol. 3, no. 1, 2018.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TAI.2021.3104789, IEEE Transactions on Artificial Intelligence

[24] J. Lehman and K. Stanley, "Abandoning Objectives: Evolution through the Search for Novelty Alone," *Evolutionary Computation*, vol. 19(2), pp. 189–223, 2011.

[25] E. Meyerson and R. Miikkulainen, "Discovering evolutionary stepping stones through behavior domination," in *Proceedings of the Genetic and Evolutionary Computation Conference*. Berlin, Germany: ACM Press, 2017, pp. 139–146.

[26] L. Rothschild and R. Mancinelli, "Life in Extreme Environments," *Nature*, vol. 409, no. 1, pp. 1092–1101, 2001.

[27] C. McKay, "On Terraforming Mars," *Extrapolation*, vol. 23, no. 4, pp. 309–314, 1982.

[28] A. Hein, R. Matheson, and D. Fries, "A Techno-economic Analysis of Asteroid Mining," *Acta Astronautica*, vol. 168, no. 1, pp. 104–115, 2020.

[29] B. Kennedy and et al., "The Unknown and the Unexplored: Insights Into the Pacific Deep-Sea Following NOAA CAPSTONE Expeditions," *Frontiers in Marine Science*, vol. 6, no. 480, 2019.

[30] S. Asseng and F. Asche, "Future Farms without Farmers," *Science Robotics*, vol. 4, no. eaaw1875, 2019.

[31] D. Howard and et al., "Evolving Embodied Intelligence from Materials to Machines," *Nature Machine Intelligence*, vol. 1, no. 12, pp. 12–19, 2019.

[32] Y. Jin, "Surrogate-assisted Evolutionary Computation: Recent Advances and Future Challenges," *Swarm and Evolutionary Computation*, vol. 1, no. 1, pp. 61–70, 2011.

[33] N. Wilson, "A Robot Scientist," *Nature Reviews Genetics*, vol. 5, no. 1, p. 164, 2004.

[34] L. Roch and et al., "ChemOS: Orchestrating Autonomous Experimentation," *Science Robotics*, vol. 3, no. 1, 2018.

[35] A. Eiben, S. Kernbach, and E. Haasdijk, "Embodied ArtificialEvolution: Artificial Evolutionary Systems in the 21st Century," *Evolutionary Intelligence*, vol. 5, no. 4, pp. 261–272, 2012.

[36] L. Brodbeck, S. Hauser, and F. Iida, "Morphological Evolution of Physical Robots through Model-Free Phenotype Development," *PLOS One*, vol. 10, no. 6, 2015.

[37] M. Jelisavcic and et al., "Real-World Evolution of Robot Morphologies: A Proof of Concept," *Artificial Life*, vol. 23, no. 2, pp. 206–235, 2017.

[38] D. Rus and C. Sung, "Spotlight on Origami Robots," *Science Robotics*, vol. 3, no. 1, 2018.

[39] F. Cichos, K. Gustavsson, B. Mehlig, and G. Volpe, "Machine Learning for Active Matter," *Nature Machine Intelligence*, vol. 2, no. 1, pp. 94–103, 2020.

[40] D. Rus and M. Tolley, "Design, Fabrication and Control of Soft Robots," *Nature*, vol. 521, no. 1, pp. 467–475, 2020.

[41] M. Wehner and et al., "An Integrated Design and Fabrication Strategy for Entirely Soft, Autonomous Robots," *Nature*, vol. 536, no. 1, pp. 451–455, 2016.

[42] P. Xu and et al., "Optical Lace for Synthetic Afferent Neural Networks," *Science Robotics*, vol. 4, no. 1, 2019.

[43] B. Shih and et al., "Electronic Skins and Machine Learning for Intelligent Soft Robots," *Science Robotics*, vol. 5, no. 1, 2020.

[44] S. Terryn and et al., "Self-Healing Soft Pneumatic Robots," *Science Robotics*, vol. 2, no. 1, 2017.

[45] A. Rohit and et al., "Self Healable Neuromorphic Memtransistor Elements for Decentralized Sensory Signal Processing in Robotics," *Nature Communications*, vol. 11, no. 4030, 2020.

[46] A. Lendlein, "Fabrication of Re-programmable Shape Memory Polymer Actuators for Robotics," *Science Robotics*, vol. 3, no. 1, 2018.

[47] J. Na and et al., "Programming Reversibly Self-Folding Origami with Micropatterned Photo-Crosslinkable Polymer Trilayers," *Advanced Materials*, vol. 27, no. 1, pp. 79–85, 2015.

[48] S. Felton and et al., "A Method for Building Self-Folding Machines," *Science*, vol. 345, no. 1, pp. 644–646, 2014.

[49] S. Camazine, J.-L. Deneubourg, N. Franks, J. Sneyd, G. Theraula, and E. Bonabeau, *Self-Organization in Biological Systems*. Princeton, USA: Princeton University Press, 2001.

[50] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems.* Oxford, England: Oxford University Press, 1999.

[51] S. Kernbach, *Handbook of Collective Robotics: Fundamentals and Challenges*. Singapore: Jenny Stanford Publishing, 2013.

[52] G. Nitschke, M. Schut, and A. Eiben, "Emergent Specialization in Biologically Inspired Collective Behavior Systems," in *Intelligent Complex Adaptive Systems*. New York, USA: IGI, 2008, pp. 100–140.

[53] M. Rubenstein, A. Cornejo, and R. Nagpal, "Programmable Self-Assembly in a Thousand-Robot Swarm," *Science*, vol. 345, no. 6198, pp. 795–799, 2014.

[54] J. Werfel, K. Petersen, and R. Nagpal, "Designing Collective Behavior in a Termite-Inspired Robot Construction Team," *Science*, vol. 343, no. 6172, pp. 754–758, 2014.

[55] G. Vasarhelyi and et al., "Optimized Flocking of Autonomous Drones in Confined Environments," *Science Robotics*, vol. 3, 2018.

[56] G. Theraulaz and E. Bonabeau, "Coordination in Distributed Building," *Science*, vol. 269, no. 1, pp. 686–688, 1995.

[57] N. Michael, J. Fink, and V. Kumar, "Cooperative Manipulation and Transportation with Aerial Robots," *Autonomous Robots*, vol. 30, no. 1, pp. 73–86, 2011.

[58] S. Keating, J. Leland, L. Cai, and N. Oxman, "Toward Site-specific and Self-sufficient Robotic Fabrication on Architectural Scales," *Science Robotics*, vol. 2, no. 1, 2017.

[59] V. Pawar, R. Stuart-Smith, and P. Scully, "Toward Autonomous Architecture: The Convergence of Digital Design, Robotics, and the Built Environment," *Science Robotics*, vol. 2, no. 1, 2017.

[60] N. Bredeche, E. Haasdijk, and A. Prieto, "Embodied Evolution in Collective Robotics: A Review," *Frontiers in Robotics and AI*, vol. 5, no. 12, pp. 1–15, 2018.

[61] M. Prokopenko, "Guided Self-Organization," *HFSP Journal*, vol. 3, no. 5, pp. 287–289, 2020.

[62] R. O'Grady, A. Christensen, and M. Dorigo, "Swarmorph: Morphogenesis with self-assembling robots," in *Morphogenetic Engineering, Understanding Complex Systems*, R. Doursat, Ed. Berlin, Germany: Springer-Verlag, 2012, pp. 27–60.

[63] I. Slavkov and et al., "Morphogenesis in Robot Swarms," *Science Robotics*, vol. 3, no. 1, 2018.

[64] C. Verhoeven and et al., "On the Origin of Satellite Swarms," *Acta Astronautica*, vol. 68, no. 1, pp. 1392–1395, 2011.

[65] G. Martius, "Robustness of Guided Self-Organization against Sensorimotor Disruptions," *Advances in Complex Systems*, vol. 16(02n03), no. 1350001, 2013.

[66] L. Yaeger, "Evolution of complexity and neural topologies," in *Guided Self-Organization: Inception*, M. Prokopenko, Ed. Berlin, Germany: Springer-Verlag, 2014, pp. 415–425.

[67] J. Mouret and S. Doncieux, "Encouraging Behavioral Diversity in Evolutionary Robotics: An Empirical Study," *Evolutionary Computation*, vol. 20, no. 1, pp. 91–133, 2012.

[68] A. Cully, J. Clune, D. Tarapore, and J.-B. Mouret, "Robots that can Adapt like Animals," *Nature*, vol. 521, no. 1, pp. 503–507, 2015.

[69] S. Doncieux, N. Bredeche, J.-B. Mouret, and A. Eiben, "Evolutionary Robotics: What, Why, and Where to," *Frontiers in Robotics and AI*, vol. 2, no. 4, 2015.

[70] L. Bayindir, "A Review of Swarm Robotics Tasks," *Neurocomputing*, vol. 172, no. 1, pp. 292–321, 2016.

[71] C. Paul, "Morphological Computation: A Basis for the Analysis of Morphology and Control Requirements," *Robotics and Autonomous Systems*, vol. 54, no. 1, pp. 619–630, 2006.

[72] V. Muller and M. Hoffmann, "What Is Morphological Computation: On How the Body Contributes to Cognition and Control," *Artificial Life*, vol. 23, no. 1, pp. 1–24, 2017.

[73] H. Lipson and J. Pollack, "Automatic Design and Manufacture of Robotic Life Forms," *Nature*, vol. 406, no. 1, pp. 974–978, 2000.

[74] M. Hale and et al., "The ARE Robot Fabricator: How to (Re)produce Robots that Can Evolve in the Real World," in *Proceedings of the Conference on Artificial Life*. Newcastle, UK: MIT Press, 2019, pp. 95–102.

[75] Y. Menguc, N. Correll, R. Kramer, and J. Paik, "Will Robots be Bodies with Brains or Brains with Bodies?" *Science Robotics*, vol. 2, no. 1, 2017.

[76] E. Neftci and B. Averbeck, "Reinforcement Learning in Artificial and Biological Systems," *Nature Machine Intelligence*, vol. 1, no. 1, pp. 133–143, 2019.

[77] S. Colabrese, K. Gustavsson, A. Celani, and L. Biferale, "Flow Navigation by Smart Microswimmers via Reinforcement Learning," *Physical Review Letters*, vol. 118, no. 1, 2017.

[78] J. Bongard, V. Zykov, and H. Lipson, "Resilient Machines through Continuous Self-modeling," *Science*, vol. 314, no. 1, pp. 1118–1121, 2006.

[79] A. Cully and J.-B. Mouret, "Evolving a Behavioral Repertoire for a Walking Robot," *Evolutionary Computation*, vol. 24, no. 1, pp. 59–88, 2016.

[80] K. Chatzilygeroudis, V. Vassiliades, and J.-B. Mouret, "Reset-free Trial-and-Error Learning for Robot Damage Recovery," *Robotics and Autonomous Systems*, vol. 1, no. 1, pp. 1–19, 2017.

[81] T. Nygaard, C. Martin, E. Samuelsen, J. Torresen, and K. Glette, "Real-world Evolution Adapts Robot Morphology and Control to Hardware Limitations," in *Proceedings of the Genetic and Evolutionary Computation Conference*. Kyoto, Japan: ACM Press, 2018, pp. 125–132.

[82] D. Hendrycks, M. Mazeika, S. Kadavath, and D. Song, "Using Self-supervised Learning can Improve Model Robustness and Uncertainty," *arXiv preprint arXiv:1906.12340*, 2019.

[83] D. Pathak, P. Agrawal, A. Efros, and T. Darrell, "Curiosity-driven exploration by self-supervised prediction," in *Proceedings of the 34th International Conference on Machine Learning*, p. 2778–2787.

[84] A. Ahmadi, T. Nygaard, N. Kottege, D. Howard, and N. Hudson, "Semi-supervised Gated Recurrent Neural Networks for Robotic Terrain Classification," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 1848–1855, 2021.

[85] Y. Zhang and Q. Yang, "A Survey on Multi-Task Learning," *IEEE Transactions on Knowledge and Data Engineering*, 2021.

[86] J. Collins, S. Chand, A. Vanderkop, and D. Howard, "A Review of Physics Simulators for Robotic Applications," *IEEE Access*, vol. 9, pp. 51 416–51 431, 2021.

[87] J. Collins, D. Howard, and J. Leitner, "Quantifying the Reality Gap in Robotic Manipulation Tasks," in *International Conference on Robotics and Automation*, 2019, pp. 6706–6712.

[88] Y. Bengio, J. Louradour, R. Collobert, and J. Weston, "Curriculum learning," in *Proceedings of the 26th annual international conference on machine learning*, 2009, pp. 41–48.

[89] J. Lee, J. Hwangbo, L. Wellhausen, V. Koltun, and M. Hutter, "Learning quadrupedal locomotion over challenging terrain," *Science robotics*, vol. 5, no. 47, 2020.

[90] H. Durrant-Whyte, N. Roy, and P. Abbeel, *Distributed Robot Ensemble Control for Deployment to Multiple Sites*, 2012, pp. 201–208.

[91] J. Williams and et al., "Online 3D Frontier-Based UGV and UAV Exploration Using Direct Point Cloud Visibility," in *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 2020, pp. 263–270.

[92] N. Hudson and et al., "Heterogeneous ground and air platforms, homogeneous sensing: Team CSIRO Data61's approach to the DARPA subterranean challenge," *arXiv preprint arXiv:2104.09053*, 2021.

[93] F. Wirthmuller, M. Klimke, J. Schlechtriemen, J. Hipp, and M. Reichert, "A Fleet Learning Architecture for Enhanced Behavior Predictions during Challenging External Conditions," *IEEE Symposium Series on Computational Intelligence*, 2020.

[94] H. Ahmadzadeh and E. Masehian, "Modular Robotic Systems: Methods and Algorithms for Abstraction, Planning, Control, and Synchronization," *Artificial Intelligence*, vol. 223, pp. 27–64, 2015.

[95] A. Zhao, J. Xu, M. Konaković, J. Hughes, A. Speilberg, D. Rus, and W. Matusik, "RoboGrammar: Graph Grammar for Terrain-Optimized Robot Design," *ACM Transactions on Graphics*, vol. 39, no. 6, pp. 1–16, 2020.

[96] J. Collins, W. Geles, D. Howard, and F. Maire, "Towards the Targeted Environment-Specific Evolution of Robot Components," in *Proceedings of the Genetic and Evolutionary Computation Conference*. New York, NY, USA: ACM, 2018, p. 61–68.

[97] A. Tyrrell, E. Hart, and G. Eiben, "Special issue on toward autonomous evolution, (re)production, and learning in robotic ecosystems," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 12, no. 3, 2020.

[98] E. Buchanan and et al., "Evolution of Diverse, Manufacturable Robot Body Plans," in *IEEE Symposium Series on Computational Intelligence*, 2020, pp. 2132–2139.

[99] T. Howison, S. Hauser, J. Hughes, and F. Iida, "Reality-Assisted Evolution of Soft Robots Through Large-scale Physical Experimentation: A Review," *arXiv preprint arXiv:2009.13960*, 2020.

[100] T. Nygaard, C. Martin, J. Torresen, K. Glette, and D. Howard, "Real-world Embodied AI through a Morphologically Adaptive Quadruped Robot," *Nature Machine Intelligence*, vol. 3, no. 5, pp. 410–419, 2021.

[101] M. McEvoy and N. Correll, "Materials that Couple Sensing, Actuation, Computation, and Communication," *Science*, vol. 347, no. 6228, 2015.

[102] C. Costa, R. Gonçalves, and S. Lanceros-Méndez, "Recent Advances and Future Challenges in Printed Batteries," *Energy Storage Materials*, vol. 28, pp. 216–234, 2020.

[103] Z. Fan and et al., "Toward the Development of Printable Nanowire Electronics and Sensors," *Advanced Materials*, vol. 21, no. 37, pp. 3730–3743, 2009.

[104] D. Cellucci, R. MacCurdy, H. Lipson, and S. Risi, "1D Printing of Recyclable Robots," *IEEE Robotics and Automation Letters*, vol. 2, no. 4, pp. 1964–1971, 2017.

[105] M. Hermans and et al., "Trainable Hardware for Dynamical Computing using Error Backpropagation through Physical Media," *Nature Communications*, vol. 6, no. 6729, 2015.

[106] G. Howard, E. Gale, L. Bull, B. de Lacy Costello, and A. Adamatzky, "Evolution of Plastic Learning in Spiking Networks via Memristive Connections," *IEEE Transactions on Evolutionary Computation*, vol. 16, no. 5, pp. 711–729, 2012.

[107] A. Soltoggio, K. Stanley, and S. Risi, "Born to Learn: The Inspiration, Progress, and Future of Evolved Plastic Artificial Neural Networks," *Neural Networks*, vol. 108, pp. 48–67, 2018.

[108] G. Yang and et al., "The Grand Challenges of Science Robotics," *Science Robotics*, vol. 3, no. 1, 2018.

[109] C. Li and et al., "Terradynamically Streamlined Shapes in Animals and Robots Enhance Traversability through Densely Cluttered Terrain," *Bioinspiration & Biomimetics*, vol. 10, no. 1, 2015.

[110] E. Del Dottore and et al., "Toward Growing Robots: A Historical Evolution from Cellular to Plant-Inspired Robotics," *Frontiers in Robotics and AI*, vol. 5, no. 16, 2018.

[111] J. Daudelin and et al., "An Integrated System for Perception-driven Autonomy with Modular Robots," *Science Robotics*, vol. 3, no. 1, 2018.

[112] M. Couceiro, "An Overview of Swarm Robotics for Search and Rescue Applications," in *Handbook of Research on Design, Control, and Modeling of Swarm Robotics*. Hershey, USA: IGI Global, 2016.