Evolutionary robotics in two decades: A review

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MS received 29 August 2014; revised 1 January 2015; accepted 11 February 2015

Abstract. Evolutionary robotics (ER) has emerged as a fast growing field in the last two decades and has earned the attention of a number of researchers. Principles of biological evolution are applied in the form of evolutionary techniques for solving the complicated problems in the areas of robotic design and control. The diversity and the intensity of this growing field is presented in this paper through the contributions made by several researchers in the categories of robot controller design, robot body design, co-evolution of body and brain and in transforming the evolved robots in physical reality. The paper discusses some of the recent achievements in each of these fields along with some expected applications which are likely to motivate the future research. For the quick reference of the readers, a *digest* of all the works is presented in the paper, spanning the years and the areas of the research contributions.

Keywords. Evolutionary robotics; evolutionary control; robot morphology; body–brain design.

1. Introduction

With the advent of bio-inspired computational techniques (Brooks 1986; Beer & Gallagher 1992; Haykin 1994; Ram *et al* 1994), the interests of many roboticists bend towards the utility of these techniques in the complicated designs and control of robots. The population-based evolutionary methods iteratively learn the features of the present scenario, eventually adapt the environment and are expected to evolve out certain features which are not yet present in the initial population. This ability of the evolutionary techniques to generate super-individuals is the base for their popularity. With the work of (Sims 1994a), the *feasibility* to obtain an evolutionary process to simultaneously design robot morphology as well as robot brain has been introduced. The efficacy of the techniques in handling challenging problems of robot design and control has opened up the field of evolutionary robotics (ER) for further exploration. This paper presents a collection of works contributed in this area, classifies them for their quick representation and discusses the possible directions for future works.

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Algorithms in evolutionary robotics usually operate on a set of population (solutions), initially selected from random distribution. This set of population is then repeatedly modified according to the fitness function(s), which are formulated to express the objective(s) of a problem. The aspects of non-continuity and multimodality are catered commendably through evolutionary algorithms (EA). By providing the possibility of working through all the possible solutions and selecting the most suitable solution to a problem, EA serves as a strong platform to work upon. Commonly used evolutionary techniques in this field of ER are genetic algorithms and genetic programming. After a brief description of some selected techniques in section 2, a state-of-the-art literature review in evolutionary robotics is presented in section 3. The section categorizes the contributions made in this field into four broad areas – evolutionary robotics control, design using evolutionary computations, co-evolution of robot body and brain and the works related to the evolution of robot design and its prototype. For a quick referral by the readers, the authors have worked upon a digest of the previous works, spanned by the categories and the published years. Each part of the digest is presented through a figure. Future challenges related to evolutionary robotics are discussed in section 4 followed by a summary of the discussion.

2. Computational tools

Some of the techniques like genetic algorithm have been used to a great extent in the field of evolutionary robotics. Most of the works presented in recent years are mainly based upon the methodologies tailored out of the basic genetic algorithm. Neural networks is another majorly used tool in the evolution of the controllers. There have been other techniques applied for the field e.g. generative representation, NeuroEvolution of Augmenting Topologies (NEAT). A few of these tools have been briefly described in this section before discussing their utilization in the design and control problems.

2.1 Genetic algorithm

Genetic algorithm (GA) belongs to a large class of evolutionary algorithms which generate solutions to optimization problems using techniques inspired by natural evolution (Holland 1975; Goldberg & Holland 1988; Goldberg 1989; Michalewicz 1996; Deb 2012; Pratihari 2013). In genetic algorithm a set of population, termed as candidate-solutions of an optimization problem, is evolved over and over to direct itself towards optimal solution(s). The candidates are initially encoded in specified format depending on real or binary genetic representation. Considering the case of binary encoding, the properties of a candidate solution are represented through a corresponding string consisting of 1 or 0 at different locations.

There are basically three operators – reproduction, crossover and mutation – that are used for evolving the population to next generations, as shown in figure 1. A fitness function is employed to measure the fitness of each candidate. Reproduction operator helps in the selection of best candidates in each generation using probability based techniques. After the selection of best candidates, a mating pool is formed. Crossover operator uses this mating pool and randomly selects a site at which crossover operation has to be carried out as shown in figure 2a. At the end of the crossover operator, mutation operator is used which induces some specific features in the offspring candidates which are not present in their parent candidates. This operator flips the value of binary digit in a string as shown in figure 2b, from $1 \rightarrow 0$ or $0 \rightarrow 1$, at a location selected with a small probability. This may help the population in coming out of a local minima.

Figure 1. Flowchart of genetic algorithm.

2.2 Neural networks

Neural Networks (NN) is an information processing model that is inspired by the working of biological nervous system and process information similar to the brain (Holland 1975, 1992; Haykin 1994; Pratihari 2013). The key element of this model is the structure of its information processing system which is basically composed of a large number of highly interconnected processing elements – termed as neurons – through synapse working in unison to solve specific problems. Neural networks consists of a net of neurons (McCulloch & Pitts 1943), similar to a human being, learn by experience. A neural network is normally used to configure parameters, through a learning process, for a specific purpose such as robot's control.

In neural network, there are three important layers as shown in figure 3, namely input layer, hidden layer and output layer. The input layer consists of sensors which fetch the feedback signals from the environment and send them to the hidden layer. The elements of the hidden layer may also be connected to each other in case of recurrent neural network. Now, hidden layer processes the signal and finally sends the output signal to the output layer. Based on the

Figure 2. (a) Crossover operator, (b) Mutation operator.

Figure 3. Neural network.

resulting output, the actuators perform their actions. Flowchart in figure 1 represents the training scenario of neural networks using genetic algorithm, where dotted box represents the block of neural networks. This dotted box in figure 1 can be replaced by figure 3 to represent the process of training to neural network.

2.3 *NeuroEvolution of augmenting topologies*

NeuroEvolution of Augmenting Topologies (NEAT), developed by Ken Stanley (Stanley & Miikkulainen 2002) in 2002, is a genetic algorithm used for evolving artificial neural networks. It alters both the weighing parameters and the structure of the network to find a balance between the fitness of evolved solutions and their diversity. It applies three key steps: tracking genes with history markers to allow crossover among topologies, applying speciation (the evolution of species) to preserve innovations and developing topologies incrementally from simple initial structures. NEAT offers a solution to the problem of competing conventions in a population of diverse topologies. NEAT also demonstrates that a meaningful metric for comparing and clustering similar networks can easily be derived from the availability of historical information in the population and costly topological analysis is not necessary to speciate or mate networks. NEAT (Stanley & Miikkulainen 2002) starts with a population of simple neural networks and then adds complexity over generations by adding new nodes and connections through mutations. By evolving networks in this way, the topology of the network does not need to be known *a priori*. NEAT searches through increasingly complex networks to find a suitable level of complexity and tends to find a solution network close to the minimal necessary size. It had been confirmed from the study (Stanley & Miikkulainen 2002) that starting with a population of minimal topologies is advantageous.

2.4 *Generative representation*

Generative representation is a class of representations in which the encoded data structure of a design can be reused recursively in creating a design. This type of representation allows the robot's morphology to develop from a basic 'seed' and a set of context-free development rules. As an example, considering two rules – ' $B \rightarrow A$ ' and ' $A \rightarrow ABA$ ' – if

3. Previous works and achievements

3.1 Evolutionary robotics control

Evolutionary computational techniques, such as genetic algorithm, are applied to the neural controller for determining the optimized weights of the controller. Beer & Gallagher (1992) had applied EA in evolving an adaptive controller for a six-legged insect-like robot. For a changed environment, the controller parameters like time constants, thresholds and connection weights of neural network are evolved. Another work by (Ram *et al* 1994) utilized the strengths of EA in evolving a collision free path for wheeled robots using genetic algorithms. The navigational problem is divided into basic behaviors – move-to-goal, avoid-static-obstacles, stay-on path, etc. These behaviors are implemented in genetic algorithm to evolve collision free paths. Similar work of collision avoidance in a navigation problem is presented by Grefenstette & Schultz (1995) for a Nomad 200 mobile robot in the presence of some moving obstacles.

During 1990s, most of the researchers working in controller designs had shown interest in evolutionary techniques for automatic evolution of the controllers. Refer the digest in figure 4 for year wise representation of several contributions. Meeden (1996) worked on the controller of a 4-wheeled robot considering – avoid contact from the walls using a light source as and when required – as the fitness function in the work. During the same time, Baluja (1996) developed an EA-based neural controller using Population-Based-Incremental-Learning (PBIL). Performance of the algorithm has been tested for steering control of a mobile robot. A two-stage controller for two wheeled soccer-playing robots using genetic algorithm has been developed by Jeong & Lee (1997). In the first stage, the position of the ball, the opponents, the partners and the goal along with the actions like move, dribble or kick are considered. Then, in the second stage optimal on-off signals are considered. In many of the works presented in the late 1990s, the development

Years / Directions	Before 1995	1995–1999	2000–2004	2005–2009	2010–2014
Evolutionary Control	Beer <i>et al.</i> (1992): Using GA evolved time constants, thresholds and connection weights of neural network for six-legged insect like robot.	Grefenstette <i>et al.</i> (1995): Used GA for learning and evolved collision-free navigation of Nomad 200 mobile robot	Pratihar <i>et al.</i> (2003): NN controller for robots using evolutionary techniques.	Harvey <i>et al.</i> (2006): Presented a study on evolutionary robotics as a new scientific tool for studying cognition.	Koos <i>et al.</i> (2010,13): Evolved fitness and transferability to overcome reality gap and tested for 8-dof quadrupedal robot
	Ram <i>et al.</i> (1994): Divide navigation problem into basic behaviours. These behaviours are implemented while evolving collision free path using GA	Mataric <i>et al.</i> (1996): Used GA, GP for automated synthesis of robot controller	Kalra <i>et al.</i> (2003): neuro-genetic approach for inverse kinematics solution of a planner robotic manipulator	Baldassarre and Nolfi (2009): Analyse the strengths and weakness of direct and evolutionary approach for development of controller of autonomous robot and discussed how both techniques can be combined	Fukunaga <i>et al.</i> (2012): Evolved controller to perform high-level task on service robot using GP.
	Floreano <i>et al.</i> (1994): Used GA for learning of NN of Khepera robot	Meeden <i>et al.</i> (1996): Evolved NN based controller for 4-wheeled robot using GA.	Pires <i>et al.</i> (2004): Generated robot trajectory planning using MOGA for 2R and 3R manipulator.		Gonzalez <i>et al.</i> (2013): Evolved Khepera in simulated environment to collect cylinders, which simulates food
		Nolfi <i>et al.</i> (1995): Modified Khepera with gripper to clean arena	Nelson <i>et al.</i> (2004): worked for the maze exploration using integrating evolutionary robotic environment.		Risi <i>et al.</i> (2013): Evolved function through Hyper-NEAT that takes morphology as input and outputs NN controller fitted for the specific morphology
		Nordin <i>et al.</i> (1997): Evolved obstacle avoidance and object following behaviour for Khepera using GA			Morse <i>et al.</i> (2013): Evolved legged motion using SUPG, which evolved through NEAT.
		Smith <i>et al.</i> (1997): Evolved a vision based football playing Khepera			Chen <i>et al.</i> (2013): Proposed an evolutionary design methodology of multilayer feed forward neural networks based on constructive approach using GA
		Baluja <i>et al.</i> (1996): Used Population based Incremental Learning (PBIL) for NN controller.			
		Jeong <i>et al.</i> (1997): Evolved a two stage controller for two wheeled soccer-playing robots using GA.			
		Pratihar <i>et al.</i> (1999): Evolved fuzzy logic controller using GA for collision free navigation in presence of moving obstacles.			

Figure 4. Evolutionary control.

of various features of controller for Khepera, a miniature mobile robot, had been studied for different situations (Floreano *et al.* 1994; Nolfi & Parisi 1995; Nordin & Banzhaf 1997; Smith 1997). Very recently, the behavior evolution of Khepera in motivated environment is presented by Montes-Gonzalez & Contreras (2013), where the task is to collect and consume food cylinders based upon obesity and anorexia. In the era 2001–2009, similar strategies have been successfully implemented for the controller designs of various robotic mechanisms (Pratihar *et al.* 1999; Kalra & Prakash 2003; Nelson *et al.* 2004; Pires *et al.* 2004; Harvey *et al.* 2005). A review paper by (Pratihar 2003) presents the works on evolutionary control.

Recently, (Koos *et al* 2010, 2013) worked upon the *reality gap* that signifies the inefficiency of the simulation once transferred onto the real system. This issue prevents evolutionary robotics applications to work in real-world. The authors introduced a *simulation-to-reality disparity* (STR disparity) measure. The higher the STR disparity, the worse the transferability from the simulation to a real-time system is. Two objectives – fitness and transferability – had been considered for the first time for the evolutionary control applications. The work had been demonstrated through the controller development of a walking 8-DOF quadruped robot and for the navigation task of an e-puck robot. Some other recent works presented in the area of evolutionary robotics control are discussed in (Piltan *et al* 2011a, b, 2013; Fukunaga *et al* 2012; Saad *et al* 2012; Chen *et al* 2013; Černý & Kubalík 2013; Klaus *et al* 2013; Shenfield & Fleming 2014). The work presented so far normally involves a specific morphology for which a controller is evolved. Some of the recent developments in the area of co-evolution of morphology and controller have been discussed in a separate section. However, a recently presented study (Risi & Stanley 2013) had added a new dimension in this field of evolutionary control, through a method called Hypercube-based NeuroEvolution of Augmenting Topologies (Hyper-NEAT). The strategy emphasizes on evolving a function which can present a controller for a given morphology, instead of training a controller for a particular quadruped morphology. Such a relationship is expected to help in the controller designs for a diversity of different morphologies. The work has been illustrated through three different robot morphologies which differ in the length of their legs. Some more work in this direction has been presented by (Morse *et al* 2013), addressing the challenge of maintaining long-term stability.

The field of evolutionary robotics, for a long time, has remained inclined towards the challenging tasks of robot control. The research works in this area has certainly covered various milestones and still the field is open for further intricacies, related to complex mechanisms, dynamic environments, cluttered workspaces, etc. More importantly, the controllers are required to be flexible to the environment and/or to the changes in the mechanism.

3.2 Evolutionary robotics design

Evolutionary computational techniques have been successfully applied by many researchers in robot morphology design problems. Figure 5 presents a year wise collection of some of the published works in this direction. The challenging problem of selecting a specific morphology for a given set of tasks has remained the focus of the research.

Chocron & Bidaud (1997) proposed the task-based design of modular manipulators using a two-level genetic algorithm, where the upper level is used to evolve the robotic topology and the lower level bounds the search for a subtask configuration. The solution of the upper level is used as an input to the lower level genetic algorithm. During the same time, (Chung *et al* 1997) worked for the optimal determination of link lengths of modular manipulators by using genetic algorithm. The evolutionary approach had also been applied to evolve the different 2D/3D morphologies using LEGO (Funes & Pollack 1998, 1999) components. Required morphologies are selected based upon artificial selection algorithms using LEGO components.

In spite of selecting morphologies only from given set of modules or components, another generative approach is presented by (Hornby *et al* 2001a, 2003; Hornby & Pollack 2001) which is composed of grammar-like rules for generating physical systems. Generative representation is an L-System program that produces a sequence of build commands to work as an assembly procedure. A generative design specification can reuse components, giving it the ability to create complex modules from simpler ones. The work demonstrated a generative system for physical modular 2D locomotive robots.

Years / Directions	Before 1995	1995–1999	2000–2004	2005–2009	2010–2014
Evolutionary Design		<p>Chedmail <i>et al.</i> (1996): used GA to open lopp robot for morphology and to follow a given trajectory among obstacles</p> <p>Chocron <i>et al.</i> (1997): Proposed two level GA for task-based design of 3D modular manipulator.</p> <p>Chung <i>et al.</i> (1997): Link-length of task-based modular manipulator was determined through GA after determining necessary configuration</p> <p>Funes <i>et al.</i> (1998, 99): Used GA to evolve the different 2D/3D morphologies using LEGO</p>	<p>Rao <i>et al.</i> (2000): Used GA for testing isomorphism among kinematic chains and to select the best frame and input links.</p> <p>Hornby <i>et al.</i> (2001, 03): Used Generative Encoding for evolving physical, modular, locomotive robot. 2D</p>	<p>Zykov <i>et al.</i> (2007): Demonstrates robots capable of autonomous self-reproduction</p> <p>Rout <i>et al.</i> (2009): Used differential evolutionary optimization for 2-dof RR planar and 4-dof SCARA manipulators.</p>	<p>Bongard <i>et al.</i> (2011): Evolved morphology of robots in form of legs and in later stage algorithm developed gait for the legs finally evolved</p> <p>Rubrecht <i>et al.</i> (2011): Evolved a manipulator working in a highly constrained workspace of the maintenance of TBM in hostile conditions using GA</p> <p>Tolley <i>et al.</i> (2011): Presented an automated approach to stochastic modular robotics that can evolve a structure and assembly plan to achieve a target function.</p> <p>Bidaud <i>et al.</i> (2011): Used evolutionary technique using Pareto-based multi-objective genetic algorithm to design task-based redundant kinematic chain and for topological optimization of a gripper</p> <p>Chen <i>et al.</i> (2013): A methodology was proposed for the rapid hardware synthesis of embedded real-time complex system.</p>

Figure 5. Evolutionary design.

Further works on the similar pattern, for spatial robots, have been carried out by many researchers during last decade. A demonstration of a large space of possible robots, capable of autonomous self-reproduction, had been carried out by Zykov *et al.* (2007). These robots are composed of actuated modules equipped with electromagnets to selectively control the morphology of the robotic assembly. Both automatically generated and manually design morphologies have been presented in the paper. Rout & Mittal (2010) proposed a modification in the differential evolution optimization technique to incorporate the effect of noises in the optimization process and obtain the optimal design of manipulators. Optimal parameters of 2-DOF RR planar manipulator and of 4-DOF SCARA manipulator have been designed and the results have been compared using genetic algorithm with similar modifications. It had been found that less computational effort is required in the differential evolutionary optimization. An automated approach to stochastic modular robotics had been presented (Tolley *et al.* 2011) that can evolve a structure to achieve a target function.

In recent works, evolutionary methods have been applied for the design of more complicated robotic mechanisms. It can be noted that in all these works, presumptions of a specific morphology for a robot are taken *a priori*. In one of such contributions (Bongard 2011), a mechanism is evolved in the form of legs and later a gait is developed for the evolved legs. The authors have worked in the optimizational synthesis of redundant kinematic chains (Singla *et al* 2010) for working in cluttered environments. A constrained optimization problem was formulated for reaching at all given task locations while avoiding any collision of the manipulator. Later, a serial robot had been designed for the maintenance of a (Tunnel Boring Machine) TBM, for its maintenance in hostile conditions (Rubrecht *et al* 2011). Multi-objective Genetic Algorithm had been applied to handle the highly constrained environments and to preserve a good exploration space. The author's team had also explored the application of Variational principle in the optimal path planning of serial manipulators, working in cluttered workspaces (Shukla *et al* 2013). The approach involves formulating the path planning problem as a constrained minimization of a functional representing the total joint movement over the complete path. The challenges related to a large number of degrees of freedom of redundant manipulators, to collisions related to cluttered spatial workspaces and to other aspects of discrete design variables and multiple objectives have been worked upon through the evolutionary approach of genetic algorithms.

More such applications of evolutionary techniques for complicated mechanisms working in cluttered environments are worth paying attention. Further investigation is also expected for the evolutionary designs of autonomous manipulators for any given environment.

3.3 Co-evolution of morphology and brain

Introduced by the work of (Sims 1994a, b), the field of co-evolving morphologies and control has received several contributions thereafter. The work shows that a number of aspects related to one physical life-form can be connected together to obtain an optimized life-form. In this direction, (Lee *et al* 1996; Lund *et al* 1997) developed a hybrid approach to evolve both the controllers and the robot bodies simultaneously, for behavior-specified tasks, using both genetic algorithm and genetic programming.

Chocron & Bidaud (1999a, b) presented an integrated dynamic simulation for locomotive robotic systems. Types of wheels, links and joints, along with their best suitable locations are represented in genotype form. The locomotion is then evolved along with its controller using genetic algorithm. Chocron *et al* (2005) recently presented a global design approach for self-reconfigurable locomotion systems based on dynamic simulations and artificial evolution. Main objective of this approach is to obtain fully integrated robotic solutions in terms of morphology (topology and kinematics) and control (architecture and command). Both topology and control have been co-evolved through genetic algorithm. Study has been presented on different examples of modular robotic systems like rover and snakes. Similar strategies may be applied for co-evolving some complicated manipulators to be worked in cluttered environments of industries and/or for specific environments arises due to calamities. A platform can be developed for evolving the complete mechanism for a given environment along with its controller.

Inspired by biological life forms, Lipson and Pollack (Lipson & Pollack 2000; Pollack & Lipson 2000) presented the evolution of articulated robots using vertices, bars, neurons and actuators through evolutionary processes. Fitness function to evolve the robots is taken as the distance moved by the center of mass of a robot in fixed number of simulation cycles. The physical prototypes of simulated robots had been prepared and compared with the simulated ones. Similar group of researchers had also worked for the construction and control of electro-mechanical systems and for locomotive creatures (Pollack *et al* 2000; Hornby *et al* 2001b).

The three generations of robots developed by this team, namely, LegoBot, Genetically Organized Lifelike Electro-Mechanics (GOLEM) and Modularity Generative Design (Tinkerbots) have been discussed in Pollack *et al* (2001).

A stable bipedal locomotion using coupled evolution of morphology and controller for a 5-linked biped robot has been achieved by Paul & Bongard (2001). A study of effects of microscopic, midrange and macroscopic changes in mass distribution of the bipedal robots has been performed. It has been illustrated that the controller and the design can be evolved simultaneously in a single step. Further, the researchers worked on a method for isolating the effect of morphological changes on the evolved behavior of quadupedal and hexapedal body plans (Pfeifer 2002; Bongard & Lipson 2005). A co-evolutionary algorithm for inferring the topology and parameters of a wide range of hidden non-linear systems with a minimum of experimentation on the target system has also been presented. A review on works done by Lipson and Pollack's team in the field of evolutionary robotics is comprised in (Lipson 2005). Bongard (2013) had also presented a thorough review on evolutionary robotics.

A chart is presented in figure 6 to sum-up the research presented in last two decades in this direction of co-evolution of robot morphology and control. It is worth mentioning here that not much connectivity has been noticed in the works presented in this direction. The researchers have either investigated the applicability of evolutionary approaches for gait development and/or motion planning of some specific locomotive systems, or the work has been presented from algorithmic perspectives. The threads need to be woven together for possible outcomes of co-evolving several kinds of mechanisms with various levels of complexity in their controllers. The research direction possesses strength of shifting the work direction of controllers design for complicated mechanisms to just focus on desired mechanisms which can be co-evolved along with their controllers.

3.4 Physically prototyped

A few researchers tried to build the prototype using 3D printing machines and compared the results of evolved simulated robots to the prototyped ones. Figure 7 presents the upcoming research works done with real creature's development as an inherent part of evolutionary process.

In a work presented by Pollack & Lipson (2000), the physics of robots is evolved using evolutionary processes and then the corresponding physical model is prototyped using 3D printing machine to compare the performance (Hornby & Pollack 2001). This strong feature in the complete evolutionary process signifies the ability of a system to go from design to manufacturing. A pathway had been demonstrated for the first time that allows transfer of virtual diversity into reality (Lipson & Pollack 2006). The approach uses only elementary building blocks in both the design and embodiment. A set of preliminary experiments, evolving electro-mechanical systems, are worked upon – first in simulation and then in reality. Using 3D solid printing, these creatures then replicate automatically into reality where they reproduce the performance of their virtual ancestors.

Recently, a novel concept of evolution of things has been introduced (Eiben *et al* 2012) and implemented for various applications, e.g. robot companion, environment friendly organisms and evolutionary 3D printing. A 3D printing machine, known as *EvoFab*, has been developed (Rieffel & Sayles 2010; Kuehn 2012) to fabricate the robots evolved through evolutionary processes so as to cover up the gap between simulation and reality. However, the work is found in one of its kind. Further investigations are required for analyzing the applicability of the proposed concepts for realistic works. Besides, similar works can be taken ahead for co-evolving design and manufacturing methodology and/or the assembly plan, simultaneously.

Years / Directions	Before 1995	1995–2000	2001–2004	2005–2009	2010–2014
Evolutionary Morphology and Control	Sims <i>et al.</i> (1994): Pioneering the concept of combining both morphology and control using evolutionary approach	Lee <i>et al.</i> (1996): Combine morphology and control for features like walking, jumping, swimming and following using EA.	Paul <i>et al.</i> (2001): Using GA and NN achieved stable bipedal locomotion using coupled evolution of morphology and control on a 5-link biped robot	Chocron <i>et al.</i> (2005): Global design approach for self-reconfigurable locomotion systems based on evaluation by dynamic simulation and optimization by artificial evolution	Bongard <i>et al.</i> (2013): Presented a review on evolutionary robotics
		Lund <i>et al.</i> (1997): Include the robot body plan in the genotype and co-evolve the task-fulfilling behaviour and body plan using GA	Hornby <i>et al.</i> (2001): Used POL-system for generatively creating both creature morphology and neural controller	Lipson <i>et al.</i> (2005): Presented a review of work done by his team in the field of evolutionary robotics	Lee <i>et al.</i> (2013): A novel cooperative coevolution (CC)-based model predictive control (MPC) is proposed to deal with formation control problem.
		Chocron <i>et al.</i> (1999): Used GA for integrating dynamic simulation of global robotic system for locomotion in its environment for various tasks	Pollack <i>et al.</i> (2001): Presented review on LegoBot, GOLEM and Tinkerbots	Paul <i>et al.</i> (2006): Used GA to obtain periodic gait controllers for tensegrity robots	
		Lipson <i>et al.</i> (2000): Evolved the articulated robots inspired by biological life form. The robots were evolved from vertices, bars, neurons and actuators by the use of evolutionary strategies.	Bongard <i>et al.</i> (2002, 04): Presented the method for isolating the effect of morphological changes on the evolved behaviour of quadrupedal and hexapedal body plan for locomotion using GA		
		Pollack <i>et al.</i> (2000): Used GA for evolution and construction of electromechanical systems.	Stanley <i>et al.</i> (2004): competitive coevolution of robot neural controller and location of sensors and motors through NEAT.		
		Pollack <i>et al.</i> (2000): Used GA for evolution and construction of electro-mechanical systems.			

Figure 6. Co-evolution of morphology and control.

4. Motivation for future research

Most of the studies presented in the area of evolutionary robotics consider both the *evolution through generations* and the *learning of individual entities*. Although evolution and learning are two distinct forms of changes, they have strong influence on each other. It has been noted that performance of learning increases when it is combined with evolutionary techniques. Thus, the interaction between learning and evolution and their effects on each other is likely to be studied for the enhancement of the *adaptive power* of evolutionary processes.

In the area of evolutionary controller design, further investigation is needed for workability and efficacy analyses of *flexible neural controllers*. To avoid efforts required for morphology-specific controllers and to independently work upon morphologies with least botheration about

Years / Directions	Before 1995	1995–1999	2000–2004	2005–2009	2010–2014
Physical Prototyping	Devis <i>et al.</i> (1992): Discusses various type of operational prototyping which includes mainly: throwaway and evolutionary prototyping		Lipson <i>et al.</i> (2000): Evolutionary approach for designing articulated bodies and the fabricated the physical model using 3D printing machine to compare the simulation results to physical model.		Rieffel <i>et al.</i> (2010), Kuehn <i>et al.</i> (2012): Developed a machine named EvoFab – a fully embodied evolutionary fabrication.
					Eiben <i>et al.</i> (2011): A novel concept of evolution of things instead of evolution of code.

Figure 7. Physical prototyping of evolved robots.

the corresponding controller design, are the points of motivation for pursuing further research in this direction.

Adaptive controllers design strategies are expected to serve a major role in development of modular robotic mechanisms. Use of homogenous or heterogeneous modules, in any number, to develop a robotic mechanism for fulfilling certain task requirements is an extremely challenging problem, without utilization of adaptive controllers.

Apart from the co-evolution of morphology and the corresponding controller, further research would help in exploring the possibilities for co-evolution of desired robotic structure and its assembly plan. With some recent works presented for the co-evolution of a robotic arm and its motion planning, possibility of providing a plan for parts fabrication and assembly steps do exist and it needs further exploration and discussions. More complexity in robotic mechanisms with respect to extra degrees of freedom, working on legs and arms together and/or evolution of co-operative robots are some of the areas worth exploration.

With the tremendously increasing applications of robotic mechanisms, the trend of *customized robots* – which are designed and developed based on the specific task requirements – is rapidly increasing. Even with a large group of researchers working on general design strategies for various kinds of task-based robots, the bottleneck remains with the transformation of the complicated designs into real mechanisms. Co-evolution of design and fabrication parameters is expected to change the complete format of developing such smart machines. The latest innovations and upcoming possibilities in rapid prototyping techniques, automatic micro machining methodologies certainly are expected to play a strong role in co-evolution.

Emotions do play an important role, along with intelligence, in decision-making process of a human being. The aspects of *artificial emotions* have already been connected, in some studies, with the intelligence aspects like perception, planning and control. It will be better to implement in the evolutionary processes these studies on interactions of different aspects of a robotic system to evolve its appropriate cognitive architecture.

5. Summary

The paper presents a review on the contributions made by several researchers in the implementation of evolutionary techniques in robot controller design, robot body design, co-evolution of body and brain and in transforming the evolved robots in physical reality. The field of evolutionary robotics has broadened the limits on the transformation of a new robotic idea into reality. The

tasks related to design, development and control of robotic mechanisms have always remained challenging due to the involvement of complicated dynamics and unknown and/or cluttered environments. Evolutionary techniques have served as a strong platform for evolving the designs, controllers and even their combinations to cater the requirements. Through the discussion on various dimensions of this field of evolutionary robotics, the paper highlights the efficacy of evolution. To support the discussion and analysis presented in the paper, a research *digest* has been compiled and included in the paper in four separate parts.

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