Beyond Gazing, Pointing, and Reaching

A Survey of Developmental Robotics

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Abstract

Developmental robotics is an emerging field located at the intersection of developmental psychology and robotics, that has lately attracted quite some attention. This paper gives a survey of a variety of research projects dealing with or inspired by developmental issues, and outlines possible future directions.

1. Introduction

Judging from the number of recent and forthcoming conferences and symposia, there is an undeniable and increasing interest in a rapidly growing research area located at the intersection of developmental psychology and robotics that has come to be known as developmental robotics.[1] Developmental robotics constitutes an interdisciplinary two-pronged approach to robotics, which on one side employs robots to instantiate and investigate models originating from developmental psychology or developmental neuroscience, and on the other hand, seeks to design better robotic systems by applying insights gained from studies on ontogenetic development. We believe that the growth of the affinity between developmental psychology and robotics has been promoted by at least two primary driving forces:

- Engineers are seeking for novel methodologies oriented toward the advancement of robotics, and the construction of better, that is, more autonomous, and more adaptable robotic systems. In that sense, studies on infant development provide a valuable source of inspiration [2–4].

- Robots can be employed as research tools for the investigation of embodied models of action and cognition [see 5, for instance]. Neuroscientists and developmental psychologists, but also engineers, may gain considerable insights from trying to embed their models into robots. This approach is also known as synthetic neural modelling [6], or synthetic methodology [7, 8].

In many aspects developmental robotics is similar to biorobotics, which can be defined as the "intersection of biology and robotics" [9, p. 1033]. Biorobotics addresses biological questions by building physical and biomimetic models of animals, and strives to advance engineering by integrating aspects of animal biomechanics and neural control into the construction of robotic systems.

The main goals of this article are: To survey the state of the art of developmental robotics, and to motivate the use of "robots as cognitive tools." We maintain that ontogenetic development can be a source of inspiration, as well as a valid design alternative for the roboticist, and that robots represent a new, and powerful research tool for the cognitive scientist.

In the following section, we give an overview of the various concurrent research threads. After a discussion of the implications of the developmental approach for robotics research, we point to future research directions and conclude.

2. Research Landscape

This section is a survey of a variety of research projects dealing with or inspired by developmental issues. Table 2 gives a representative sampling of studies, and is not intended to be fully comprehensive. For the inclusion of studies we adopted the two following criteria:

- The study had to provide clear evidence for robotic experiments. Computer-based models of real systems, such as avatars, or other sophisticated simulators, were discarded *a priori*. In other words, the system had to be situated in the real world, since only the world crystallizes the "really hard" issues [10].

- The study had to show a clear intent to address hypotheses put forward in either developmental psychology or developmental neuroscience. The use of connectionist models, reinforcement or incremental

[1] Developmental robotics and Epigenetic robotics are very similar research endeavours. They share problems and challenges, and have a common vision. Epigenetic robotics focuses primarily on cognitive and social development [1]. Developmental robotics encompasses a broader spectrum of issues, and investigates also morphological development, and the acquisition of motor skills.

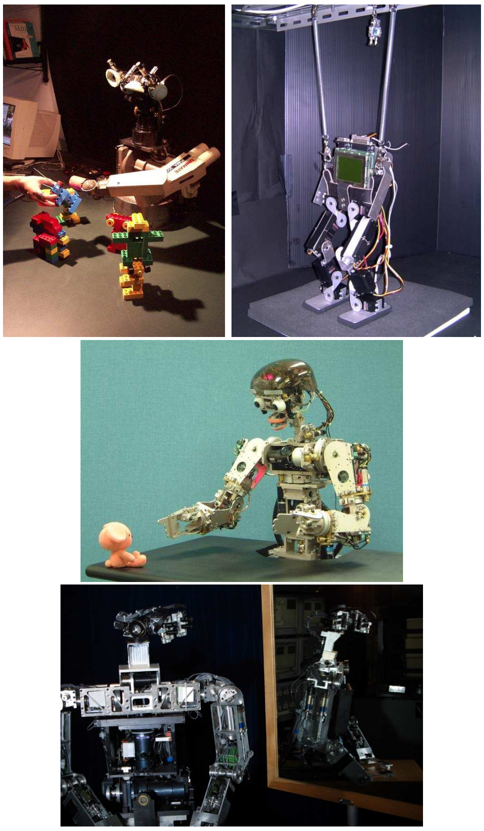

Figure 1: Examples of robots used in developmental robotics: BabyBot (LiraLab), BabyBouncer (AIST), Infanoid (CRL), COG (MIT).

learning applied to robot control alone – without any link to developmental theories, for instance – did not fulfill this requirement.

Despite the admittedly rather restrictive nature of these two requirements, we were able to identify quite a number of research papers satisfying them. In order to provide some structure, we proceeded with clustering the selected papers according to their primary interest areas: (1) social interaction; (2) sensorimotor control; (3) categorization; (4) value system; (5) developmental plasticity; (6) motor skill acquisition and morphological changes. This grouping in 6 primary interest areas may seem rather arbitrary. As a matter of fact, the borders of the various categories are not as clearly defined as this classification might suggest. Nevertheless, we think that it is useful for the assessment of a rapidly growing research area.

2.1 Social interaction

Studies in social interaction and acquisition of social behaviors in robotic systems have looked at a wide range of learning situations and techniques. Prominent research areas are mechanisms of shared or joint attention, low-level imitation (reproduction of simple and basic movements), social regulation, and development of language – for a thorough review on "socially interactive robots", see Fong et al. [38].

Scassellati [19, 39], for instance, described the early stages of the implementation of a mechanism of shared attention in a robotic system based on a model suggested by Baron-Cohen [40]. He advocated a developmental methodology as a means of providing a structured decomposition of complex tasks and facilitating learning. Another developmental model of joint attention was implemented by Nagai et al. [18]. The model involved the development of the sensing capabilities of a robot from an immature to a mature state, and a change of the caregiver's task evaluation criteria. The "rudimentary" or early type of joint visual attention displayed by infants was investigated by Kozima et al. [16].

An architecture for a mutually regulatory human-robot interaction was reported by Breazeal and Scassellati [12]. The suggested framework strove to integrate various factors involved in social exchanges, e.g., perception, attention, motivations, and expressive displays, so as to to create a suitable learning context for a social infant-like robot capable of regulating the intensity of the interaction. Although the implementation did not parallel infant development exactly, the authors claimed that "the systems design was heavily inspired by the role motivations and facial expressions play in maintaining an appropriate level of stimulation during social interaction with adults" [12, p. 51]. Along a similar line, Dautenhahn and Billard [14] discussed the emergence of global interaction patterns through exploitation of movement dynamics in the case of human-robot interaction. The authors based their experiments on an influential theory of cognitive development proposed by Vygotsky [41], which states that social interactions are of essential importance for the development of individual intelligence.

Socially-situated learning guided by robot-directed speech is discussed in Breazeal and Aryananda [13]. The robot's affective state – and as a consequence its behavior – is influenced by means of verbal communication with a human caregiver. The paper explores recognition of affective communicative intent without the need to associate a meaning to what is said, but just via the extraction of particular cues typical of infant-directed speech [42]. Varshavskaya [20] applied a behavior-based approach to the problem of early concept and vocal label acquisition in a sociable robot. The goal of the system was to generate "the kind of vocal output that a prelinguistic infant may produce in the age range between 10 and 12 months, namely emotive grunts, canonical babblings, and a formulaic proto-language." The synthesis of a robotic protolanguage through interaction of a robot either with human or a robotic teacher was also investigated by Dautenhahn and Billard [14].

Recently, *developmentally inspired* approaches to robot imitation have received considerable attention [11, 15, 17]. Many authors suggested a relatively straightforward two-stage procedure: First, associate proprioceptive

Subject area	Goal/Focus	Robot	References
Social interaction	low-level imitation	MR+AG	Andry et al. [11]
(Basic social competencies)	social regulation	AVH	Breazeal and Scassellati [12]
	regulation of affective communication	AVH	Breazeal and Aryananda [13]
	language development	MR	Dautenhahn and Billard [14]
	low-level imitation	AVH	Demiris [15]
	joint visual attention	UTH	Kozima et al. [16]
	early imitation, self-learning	UTH+MR	Kuniyoshi et al. [17]
	joint visual attention	UTH+MR	Nagai et al. [18]
	joint shared attention	UTH	Scassellati [19]
	early language development	AVH	Varshavskaya [20]
Sensorimotor control	saccading, gaze fixation	AVH	Berthouze et al. [21]
(Basic motor competencies)	visuo-haptic exploration	HGS	Coehlo et al. [22]
	hand-eye coordination	UTH	Marjanovic et al. [23]
	visually-guided reaching	UTH	Metta et al. [24]
	visually-guided manipulation	UTH	Metta and Fitzpatrick [25]
	eye-arm coordination	RA	Stoica [26]
	indoor navigation	MR+AG	Weng et al. [27]
Value system	invariant object recognition	MR+AG	Krichmar and Edelman [28]
	category learning	MR+AG	Pfeifer and Scheier [29]
	perceptual categorization	MR+AG	Sporns et al. [30]
	neuromodulation	MR+AG	Sporns and Alexander [31]
Categorization	sensorimotor categorization	AVH	Berthouze and Kuniyoshi [32]
	invariant object recognition	MR+AG	Krichmar and Edelman [28]
	sensorimotor categorization	MR+AG	Scheier and Lambrinos [33]
developmental plasticity	role of behavioral interaction	MR+AG	Almassy et al. [34]
	obstacle avoidance, sensory deprivation	MR	Elliott and Shadbolt [35]
	perceptual categorization	MR+AG	Sporns et al. [30]
Motor skill acquisition	pendulation, morphological changes	HD	Lungarella and Berthouze [36]
	bouncing	HD	Lungarella and Berthouze [37]

Figure 2: Representative examples of developmentally inspired robotics research. AVH = Active Vision Head, UTH = Upper-Torso Humanoid, MR = Mobile Robot, HD = Humanoid, HGS = Humanoid grasping system, UTH+MR = Upper-Torso Humanoid on Mobile Platform, MR+AG = Mobile Robot equipped with Arm and Gripper.

or motor information to the corresponding visual percepts and then, while imitating, exploit the previously acquired associations by querying for the motor commands that correspond to the observed visual percept. Learning by imitation offers many benefits [15, 43]. A human demonstrator, for instance, can teach a robot to perform certain type of movements by simply performing them in front of the robot. This strategy reduces drastically the search space for the task that the agent is trying to solve and speeds up learning [43]. Furthermore it is possible to teach new tasks to robots by interacting naturally with them. This is appealing, and might lead to open-ended learning not constrained by any particular task-environment. Inspired by the Active Intermodal Matching hypothesis for early infant imitation [44], which proposes that infants try to match visual information against appropriately transformed proprioceptive information, Demiris [15] developed a computational architecture of early imitation used for the control of an active vision head. The author also gives an overview of previous work done in the field of robotic imitation [see also 45]. Usually the robot imitates the human teacher. Stoica [26] reversed this relationship, and showed that imitation of the human (teacher) by the robot, could lead naturally to eye-arm coordination as well as sensible control of the arm.

2.2 *Sensorimotor control*

For embodied systems to behave and interact in the real world, an appropriate coordination of action and perception is necessary. It is commonly accepted that action and perception are tightly intertwined, and that the refinement of the coupling is the outcome of a gradual developmental process. Accurate motor control would not be possible without perception, and vice versa, purposive vision would not be feasible without adequate actions. This holds for the coordination of vision and motor control in particular, and sensorimotor coordination in general.

There are a few examples of application of a developmental approach to the acquisition of visuo-motor coordinations: Marjanovic et al. [23], for instance, were able to show how acquired oculomotor control (saccadic movements) could be reused for learning to reach or point toward a visually identified target. A similar model of developmental control of reaching was investigated by Metta et al. [24]. Their conclusion was that reflexes might speed up learning and considerably simplify the problem of the exploration of the workspace. They also pointed out that control and learning should proceed concurrently rather than separately – as it is the case in more traditional engineering approaches.

A slightly different research direction was taken by Coehlo et al. [22]. They proposed a system architecture that employed haptic categories and the integration of tactile and visual information to learn to predict the best type of grasp for an observed object. Of relevance is the autonomous development of complex visual features starting from simple primitives.

Berthouze et al. [21] employed imitation to teach an active vision head simple visual skills, that is, gaze control, and saccading movements. Remarkably, the robot even discovered its "own vestibulo-ocular reflex." The approach capitalized on the exploitation of the robot-environment interaction and the emergence of coordinated behavior. Interaction was also central in the study performed by Metta and Fitzpatrick [25]. Starting from a minimal set of hypotheses, their humanoid system learned by actively poking and prodding objects (e.g., a toy car or a bottle) the behavior of the object associated with a particular manipulation of it (e.g., a toy car rolls along if pushed appropriately, while a bottle tends to roll sideways). Their results were in accordance with the theory of Gibsonian affordances [46].

A *developmental algorithm* tested on a robot that had to learn to navigate on its own in an unknown indoor environment is described in Weng et al. [27]. The robot was trained interactively, that is, on-line and in real time, via direct touch of one of the 28 touch sensors located on the robot's body. By receiving some help and guidance from a human teacher, the algorithm was able to automatically develop low-level vision and touch-guided motor behaviors.

2.3 Categorization

Traditionally, the problem of categorization has been investigated by employing disembodied categorization models [for an overview on the issue, *cf.* 7]. However, a growing body of evidence supports a more interactive, dynamic, and embodied view of how categories are formed. Embodied models of categorization are not passively exposed to sensory data, but through movements and interactions with the environment, they are able to generate "good" sensory data, for example by inducing time-locked spatio-temporal correlations within one sensory modality or across various sensory modalities [see 47]. In this sense, this area of research represents a subset of the one related to sensorimotor control.

Categorization of objects via real-time correlation of temporally contingent information impinging on the robot's haptic and visual sensors was achieved by Scheier and Lambrinos [33]. The suggested robot control architecture employed sensorimotor coordination at various functional levels – for saccading on interesting regions in the environment, for attentional sensorimotor loops, and for category learning. Sensorimotor activity was also critical in work performed by Krichmar and Edelman [28], who studied the role played by sensory experience for the development of perceptual categories. In particular, the authors showed that overall frequency and temporal order of encountered perceptual stimuli had a definite influence on the number of neural units devoted to a specific object class.

A sensorimotor-related (not object-related) type of categorization is reported in [32]. The authors used self-organizing Kohonen maps to perform an unsupervised categorization of sensorimotor patterns, which emerged from embodied interaction of an active vision system with its environment. The self-organization process led to four sensorimotor categories consisting of horizontal, vertical, and "in-depth" motions, and an intermediate not clearly defined category.

2.4 Value system

There have been a number of explicit realizations of value systems in robotics. In all those implementations the value system played either the role of an internal mediator of salient environmental stimuli and events, or was used to guide some sort of exploration process. A learning technique in which the output of the value system modulates the learning itself is called value-based or value-dependent learning. Unlike reinforcement learning, value-based learning schemes specify the neural mechanisms by which stimuli can modulate learning [5, 7]. Another difference between the two learning paradigms is the fact that typically, in reinforcement learning, learning is regulated by a (reinforcement) signal given by the environment, whereas in value-based learning, this (value) signal is an output of the agent's value system.

Almassy et al. [34] constructed a simulated neural model, one of whose four components was a "diffuse (ascending) value system" (p. 347), and embedded it in autonomous real-world device. The value signals were used to modify the strength of the connections from the neurons of the visual area to the ones of the motor area. One of the results of these value-dependent modifications was that without any supervision, appropriate behavioral actions could be linked to particular responses of the visual system. A similar model system was described by Krichmar and Edelman [28] (see *Categorization*). Compared to previous work, the modeled value signal had two additional features: (a) its prolonged effect on synaptic plasticity, and (b) the presence of time-delays [28, p. 829]. Another instantiation of a value system, whose output was used as a gating signal to modulate Hebbian learning, is described in [29, 33] (see *Categorization*).

Sporns and Alexander [31] tested a computational model of a neuromodulatory system [2] in an autonomous

[2] Neuromodulatory systems are instantiations value systems that find justification in neurobiology. Examples include the dopaminergic and the noradrenergic systems.

robot. The model comprised two neuromodulatory components mediating the effect of rewards and of aversive stimuli. According to the authors, value signals play a dual role in synaptic plasticity, since (a) they modulate the strength of the connection between sensory and motor units, and (b) they are responsible for the change of the response properties of the value system itself.

In contrast to the previous cases, where the value system was used to modulate learning, Lungarella and Berthouze [36] employed the value system to direct the exploration of the parameter space associated with the action system of a robot that had to learn to pendulate.

2.5 Developmental plasticity

The developing brain is plastic, and its plasticity is experience-dependent.

Almassy et al. [34] analyzed how environmental interactions of a simulated neural model embedded in a robot may influence the initial formation, the development and dynamic adjustment of complex neural responses during sensory experience. They observed that the robot's self-generated movements were crucial for the emergence and development of selective and translation-invariant visual cortical responses, since they induced correlations in various sensory modalities. Another result was the development of a foveal preference, that is, "stronger visual responses to objects that were presented closer to the visual fovea" [34, p. 358].

A further example of "synthetic neural modeling" is illustrated in [35]. The authors studied the application of a neural model, featuring "anatomical, activity-dependent, developmental synaptic plasticity" (p. 167), to the growth of a sensorimotor map in a obstacle-avoiding mobile robot. They concluded that the deprivation of one or two receptors can be taken care of by a mechanism of "developmental plasticity", which according to the authors would "permit a nervous systems to tune itself to the body in which it finds itself and to the environment in which the body resides" (p. 168).

2.6 Morphological changes and motor skill acquisition

Morphological changes (e.g., body growth) represent one of the most salient and explicit characteristics of ongoing developmental processes.

Lungarella and Berthouze [48] investigated the role played by those changes for the acquisition of motor skills by using a small-sized humanoid robot that had to learn to pendulate, i.e., to swing like a pendulum. The authors attempted to understand whether physical limitations and constraints inherent to body development could be beneficial for the exploration and selection of stable sensorimotor configurations [see also 49, 50]. In [48], they report on a comparative analysis between outright use of two bodily DOFs, and a progressive release of those two DOFs by employing a mechanism of developmental freezing and unfreezing of DOFs [51]. In a follow-up case-study, Lungarella and Berthouze [36] investigated the hypothesis that inherent adaptivity of motor development leads to behavioral characteristics not obtainable by mere value-based regulation of neural parameters. The authors were able to show that the outright use of two of the available DOFs reduced the likelihood for physical entrainment (i.e., mutual regulation of body and environmental dynamics) to take place. This in turn led to a reduced robustness of the system against environmental perturbations.

Inspired by an investigation conducted by the developmental psychologist Eugene Goldfield and his collaborators [52], Lungarella and Berthouze [37] performed a series of experiments by employing a humanoid robot, which was strapped in a *Jolly Jumper* infant bouncer (see Fig.1) – a popular toy for infants. In the authors' own words, the main motivation for the study was the exploration of the mechanisms underlying the emergence of movement pattern from the self-exploration of the sensorimotor space, starting off with seemingly random, spontaneous movements. The results presented in the study are of preliminary nature only.

3. Developmental robotics: existing theories

Early theorization of developmental robotics can be traced back to Brooks [10] and Brooks and Stein [53]. Sandini et al. [54] were among the first to recognize how crucial it is to take into account development if we are off to understand human intelligence. They called their approach *Developmental Engineering*. As in the engineering tradition of building things, it was directed toward the definition of a theory for the construction of complex systems. The main objective was to show that "the adoption of a framework of biological development would be suitable for the construction of artificial systems" [24, p. 1]. In [3], the author pointed out that this activity can be envisaged as a new tool for exploring developmental cognitive sciences. Such a "new tool" has a similar role to what system and control theory had for the analysis of human movements. The authors explored some of the aspects of visuo-motor coordination in a humanoid robot called Babybot (see Fig.1). Issues, such as the autonomous acquisition of the training data, the progressive increase of the task complexity (by increasing the visual resolution of the system), and the integration of various sensory modalities, have been explored [see 55, 56, for instance]. They also produced a *manifesto* of developmental robotics where various aspects relevant to the construction of complex autonomous systems were described [57]. In their view, the ability of recognizing longer and more complicated chains of cause-effect relationships might characterize learning in an ecological context. In a natural setting no teacher can possibly provide a detailed learning signal and enough training data (e.g., in motor learning the correct activation of all muscles, proper torque values, and so on).

Around the same time, in *Alternative Essences of Intelligence*, Brooks et al. [2] explored four "intertwined key attributes" of human-like intelligent systems: development, embodiment, social interaction, and multi-sensory integration. Negating three central implicit beliefs of classical AI, they made the following assumptions: (a) human intelligence is not as general purpose as usually thought; (b) it does not require a monolithic control system (for the existence of which there is no evidence); and (c) intelligent behavior does not require a centrally stored model of real world. The authors, drawing inspiration from developmental neuroscience and psychology, performed a series of experiments, in which their humanoid robot had to learn some fundamental sensorimotor and social behaviors. More to the point of our review, Scassellati [39] proposed that a developmental approach – in humans as well as in robots – might provide a useful structured decomposition when learning complex tasks, or in his own words: "Building systems developmentally facilitates learning both by providing a structured decomposition of skills and by gradually increasing the complexity of the task to match the competency of the system" [39, p. 29]. The same group at MIT tried to capitalize on the concept of bootstrapping of skills, i.e., the layering of new skills on top of existing ones. Also, the gradual increase in complexity both of task-environment, sensory input (through the simulation of maturational processes), and motor control was explored in tasks such as learning to saccade and to reach toward a visually identified target [23] (see previous section).

Another example of this novel and developmentally inspired approach to robotics is given by [4]. The authors proposed a theory for the design and construction of humanoid systems called *Cognitive Developmental Robotics* (CDR). The key aspect of CDR is to avoid implementing the robot's control structure "according to the designer's understanding of the robot's physics" [4], but to have the robot acquire its own "understanding through interaction with the environment" (p. 185). This departs from traditional control engineering, where the designer of the system imposes the structure of the controller. In CDR in particular, and in developmental robotics in general, the robot has to get to grips with the structure of the environment and behavior, rather than being endowed with an externally designed structure. CDR also points out at how to "prepare" the robot's environment in order to progressively teach the robot new and more complex tasks without overwhelming its artificial cognitive structure. This is scaffolding, i.e., the process by which parents support and guide the development of infants.

A last example of "existing theories" in developmental robotics is *Autonomous Mental Development* (AMD) [58]. Inspirational also in this case was human development. The main difference from the traditional approach is the fact that in the first case, the task is "understood by the engineer", whereas in the second case, it is the machine that has to develop its own understanding of it. AMD relegates the human to the role of teaching and supporting the robot through reinforcement signals. The requirements for a truly mental development include being *non-task specific*, because the task is generally unknown at design time. For the same reason, the artificial "brain" has to develop a representation of the task which could not be possibly embedded *a priori* by the designer. It is foreseen that open-ended learning might be obtained if algorithms are devised following these guidelines.

4. Discussion and Future Directions

A number of observations can now be made. Almost 60% of the reviewed studies (16 out of 28) fell either in the category *social interaction* or the one related to *sensorimotor control* (as is evident from Table 2). These two categories constitutes primary directions of research in developmental robotics.

As a matter of fact, quite some studies have lately been directed toward designing socially interactive robots. In a very recent and broad overview of the field, Fong et al. [38] – trying to seek for an answer to the question: "why socially interactive robots?" – maintained that "social interaction is desirable in the case robots mediate human-human [peer-to-peer] interactions or in the case robots function as a representation of, or representative for, the human [3] " (p. 4). We believe that in order to acquire more advanced social competencies (e.g., deferred imitation), it may be desirable to endow the robot with mechanisms that enable it to go through a process of progressive development of social skills. This opinion is shared by Fong et al. [38].

Brooks [59] emphasized the "crucial" importance of *basic social competences* for peer-to-peer interactions, such as gaze-direction or determination of gaze-direction. Early motor competencies are a natural prerequisite for the development of basic social competencies. Hence it is not surprising that another area of big interest is the one related to *sensorimotor control*, in particular, basic visuo-motor competencies, such as saccading, gaze fixation, hand-eye coordination, visually-guided reaching, and so on. However, we were able to single out only a few studies on *motor skill acquisition* that have attempted *to go beyond gazing, pointing, and reaching*, i.e., early motor competencies. In many ways, the spectrum of outstanding research issues, as well as the complexity of our robots, have considerably increased over the past few years, but not many "developmental" reconnaissance tours into unexplored research directions have been attempted.

The problem of learning to control many degrees of freedom, for instance, is important, and imitation learning may be indeed the best route to its solution [43].

[3] According to [59, p.135], remote-presence robots may be the killer application for robots in the short term.

From a developmental perspective, learning multi-joint coordinations or the acquisition of complex motor skills may benefit from the introduction of initial morphological constraints, which over time are gradually released [36, 39]. In the same context, mechanisms of physical and neural entrainment, that is, mutual regulation between environment and the robot's neural and body dynamics, as well as value-based self-exploration of body and neural parameters, also deserve further investigation. A promising approach that attempted to capitalize on the interplay between neural plasticity, *morphological changes*, and entrainment to the intrinsic dynamics of body and task, was promoted by Lungarella and Berthouze [36].

Another research issue that needs further attention is autonomy, i.e., through self-supervision (independently from human programming and intervention), the robot should forge its own motivational and value systems. For an artificial system to be truly autonomous, "the mechanisms that mold local structure to yield global function must reside wholly within the system itself" [5]. In other words, the system must be self-contained. We believe that the adoption of value-based learning schemes may be a step in the right direction. Metta and Fitzpatrick [25], for instance, were able to show that a mirror neurons-like structure involving basic object recognition is of relevance for an artificial system when it has to collect training data autonomously.

Categorization (thought to be one of the cornerstones of cognitive development) has also proven to be a hard problem. And casting it in a developmental light may be advantageous, as shown by [28, 31, 34].

To conclude the paper, we believe that the big challenge for the future will be to *go beyond gazing, pointing, and reaching*. In order to guarantee truly autonomous behavior, the robots of the future will have to be endowed with better sensory and motor apparata, more refined value-based learning mechanisms, and means of exploiting neural and body dynamics.

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