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Computational Intelligence Techniques in Bio-inspired Robotics

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Abstract. Biologically inspired robotics is a rapidly emerging research area standing at the cross-cut of biology, artificial intelligence, and robotics. The structural and functional perfection of the biological creatures achieved through thousands of years of evolution in nature have made them a great source of inspiration for designing complex autonomous systems. Accordingly, robotics researchers have initiated designing artificial machines while considering the characteristics of biological systems as the benchmark knowledge. 'Biomimetics', an emerging research area, is a consequence of such initiatives. Bio-inspired robotics is actually a subset of biomimectics focusing mostly on the design of autonomous robots while mimicking the intelligence, cognition, and structural properties of the primates and other lower order species. Computational intelligence techniques developed in the past several years are related closely to bio-inspired robotics as both of them have originated from the common inspiration of mimicking human intelligence, although their development have followed different paths. Bio-inspired robotics have used computational intelligence techniques to mathematically model 'human-like intelligence behavior' for autonomous robots. This chapter provides an overview on the tools of computational intelligence and their applications in bio-inspired robotics. It highlights the recent progress made in bio-inspired robotics while giving a special emphasis on the usage of computational intelligence tools to design human-like cognitive abilities in the robotic systems.

1.1 Introduction

Biologically inspired robotics is a multidisciplinary research area motivated by the inspiration of using nature as the benchmark in designing complex autonomous systems and, at the same time, benefiting nature with the improved system autonomy. Biological creatures, with their adaptability, structural sophistication and varieties in behavior, have always been a great source of inspiration for the researchers in robotics. But substantial research in bio-inspired robotics has started only a few years back. The reasons behind such a delayed start is mainly due to our limited understanding of nature, and to the lack of technological sophistication to mimic biological systems, both at the structural as well as the intellectual level. During the past two decades we have achieved remarkable improvement in closely pertinent areas of bio-robotics such as nano-technology, artificial intelligence (AI), and neuroscience. Achievements in these three, apparently disjoint, disciplines have placed us in a position to perform reverse engineering on biological systems. Increased computing power in gradually diminishing sized computer chips are showing the glimpse of possibility of having computers

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comparable to the primates brain (could be lower order primates) in terms of processing power, complexity, and compactness. Our steadily developing understanding of living elements, especially the mechanism of brain functions, theory of interaction among mind, body, and brain, is opening up possibilities of mimicking them in a more robust manner. The AI and related disciplines have already earned remarkable improvement in developing sophisticated computational tools, industry-strength algorithms for machine learning, image, and speech processing which may help to successfully model the functionality of biological systems. At the midst of resonance in development among the related disciplines, bio-inspired robotics has become a topic of significant interest. A substantial amount of research work has been reported during the current decade in various sub-disciplines of bio-inspired robotics and the flow is continuously rising.

This chapter provides a brief survey on the trends of bio-inspired robotics while giving a special focus on how its development has been influenced by the approaches rooted in computational intelligence (CI). The rest of the chapter is organized as follows. Section 1.2 sheds light on the history of AI, bio-inspired robotic, and CI techniques, their common origin and underlying goals. Section 1.3 provides a brief discussion on bio-inspired robotics as an emerging research area and highlights existing research directions in bio-inspired robotics. Section 1.4 focuses on one of the most appealing branch of bio-inspired robotics namely, cognitive modeling for autonomous robots. It focuses on different emerging areas of cognitive modeling for autonomous robots, provides a brief survey on the state-of-the art of these areas and sheds light on the role of CI techniques in designing artificial cognition for autonomous robots. Finally, section 1.5 draws some concluding comments.

1.2 Bio-inspired Robotics and Tools of Computational Intelligence: The Historic Synergy

1.2.1 Overview

Computational intelligence techniques, e.g. neural networks, fuzzy logic, genetic algorithms, probabilistic algorithms, are well known to be biomimetic computational tools designed from the inspiration of mimicking the structural and functional elegance of the human to perceive the environment and act accordingly while applying their intelligence. On the other hand, the dream of a human-like machine (in terms of structure and intelligence) was there since the birth of AI. The CI techniques and AI, therefore, should have been complementing each other in the course of their own development as well as in building a complete model of human-like intelligence. In reality, however, a different scenario has taken place. The development of CI techniques followed a different path than that of the AI [1]. The CI techniques have experienced tremendous theoretical growth over the past few decades and have also earned popularity in application areas e.g. control, search and optimization, data mining, knowledge representation, signal processing, and robotics. Specifically in AI robotics, a good number of robotic systems uses CI techniques for robust control, planning, and decision making [2, 3, 4, 5]. Unfortunately, these applications do not reflect the vision with which the CI techniques were originally developed for: modeling human intelligence [6]. The AI, on the other hand, ruled by the norms of GOFAI(R) (Good Old Fashioned AI (and Robotics)) [7, 8] for an extended period of time, failed in many ways to utilize the power of CI techniques in designing human-like intelligence. Thus the long-expected synergy between AI and CI was delayed until the AI revolution of 1990s [9] which replaced the static notion of " 'mind-as-computer' in a symbol-based representation of the world" with the dynamic idea of 'embodied cognition'. Embodied cognition advocates the notion of bidirectional active interaction among body, mind, and environment as the building block of developing intelligence, both natural and artificial [9, 10, 11, 12, 13]. The current AI robotics, therefore, is focusing on modeling the highly complex, non-linear interaction among mind, body, and environment, the self-motivation to build knowledge base, the automated reasoning, and decision making. The ideas of embodied cognition places CI techniques back in the stage of AI. The CI tools blend naturally with these concepts as they share the common principles of biology. The CI techniques, therefore, are very efficient tools to design bio-inspired intelligence in autonomous robots.

1.2.2 The CI Tools Most Commonly Used in Bio-inspired Robotics

The CI tools developed in the past several years have been widely used in different branches of bio-inspired robotics. New research challenges with higher complexities are arising as we are approaching toward the goal of designing human-like intelligent machines. To meet these challenges new CI tools are being developed as well as modification of the existing tools are being performed. For instance, artificial immune algorithm [14] has been developed based on the inspiration of human immune systems and type 2 fuzzy logic [15] has been proposed as an extension of tradition fuzzy logic to include probabilistic uncertainty in fuzzy reasoning. A brief introduction on the CI tools most commonly used in the existing bio-robotics literature is provided here.

1.2.2.1 Artificial Neural Network

Artificial neural network (ANN) is one of the most commonly used CI tools in bio-inspired robotics [16]. ANNs mimic the highly parallel structural connectivity and non-linear operating principle of the brain cells (known as neuron) of biological creatures [17]. The structure of a single artificial neuron (also known as perceptron) is very simple: input terminal(s), one output terminal, and a function defining the mapping from input(s) to the output. The simple perceptrons connect with each other in layered architectures to form different kind of neural networks which are generally capable to handle even very high degree of non-linearity. One elegant property of ANNs is they allow the exact pattern of non-linearity to emerge within themselves through the process of training. There are algorithms to conduct efficient training of ANNs. The theories of neural network have gone through several facets of development in the past decades resulting in varieties of ANNs suitable for different application areas, e.g. data mining, robotics, communication.

1.2.2.2 Fuzzy Reasoning

Fuzzy reasoning is another CI tool which mimics the capacity of human mind to process partial truth in observed phenomena [18]. Fuzzy logic, the mathematics of fuzzy reasoning, advocates that the traditional crisp (or binary) logic which deals with the two extreme ends ('yes'and 'no') of the decision paradigm is just a special case of fuzzy logic. Fuzzy reasoning, therefore, is governed by the norms of partial membership and assigns a degree belief in favor of a proposition. Such degree of belief may take any value between zero to one. The elegance of fuzzy logic lies in its simplicity to model even extremely complex, high-dimensional decision problems. This results in its widespread application in areas such as control, pattern recognition, artificial intelligence, and robotics.

1.2.2.3 Evolutionary Algorithms

Evolutionary algorithms (EA) are generally considered as search and optimization technique inspired from the principle of natural selection. They provide a structured way to locate the most suitable solution in a highly complex search landscape. EAs generally perform a series of operations (selection, mutation, crossover) to iteratively optimize a fitness function. Starting form the simple form as proposed in [19], the evolutionary algorithms have went through numerous modifications to suit with the increasing complexities of todays search problems. A number of new search and optimization algorithms has been developed in recent years based on the inspiration from nature, e.g. artificial immune algorithm [14], swarm intelligence [20], ant-colony optimization [21]. The application of EAs in bio-inspired robotics is still relatively less appealing due to its high time complexity.

1.2.2.4 Probabilistic Algorithms

Probabilistic algorithms have been quite useful in several areas of mobile robotics including bio-inspired robotics. This is because of their capacity to deal with the uncertainty inherent in real-world robotic problems [22]. The probabilistic algorithms used in bio-inspired robotics are generally related to Bayesian inference, Bayes network and different variants of Bayes filter [23, 24, 25]. The mechanism of posterior formation based on prior knowledge and observation likelihood makes Bayes theorem a suitable candidate in modeling intelligence behavior for robotics systems. Besides, the mathematical structures of Bayes network and Markov model are well suited for state based robotic systems.

1.3 Bio-inspired Robotics: An Emerging Research Field

Bio-inspired robots are a new kind of research platforms developed to fulfill the two-pronged desire of humans: enhancing the quality of human life by incorporating artificial systems in it and, at the same time, improving the system design through integrating biology with it. The major driving forces behind the research on bio-inspired robotics, therefore, can be summarized as follows.

- **Robots to assist human:** During the last decade mobile robotics has experienced a significant forward shift toward real-world applications from the laboratory based research. The Mars rover mission [26], winning of DARPA grand challenge 2005

[27], robotics application in surgery [28] and health care [29] are among few examples. The bio-inspired robots are expected to top the current successes of mobile robots with their human-like sophistication in perception, reasoning, decision making and locomotion. These robots will be able to adapt autonomously in changing environment, will apply learned knowledge and reasoning capacity to solve new problems, and above all will be able, to a large extent, to take care of themselves [30]. This sort of machines have potential to drastically improve the quality of human life through providing assistance in several areas such as search and rescue, mining, space-applications, military- surveillance, entertainment, surgery, and health care.

- **Robots to understand human:** The other inspiration of bio-inspired robotics is to have a better understanding of the capacities that the humans are blessed with [31]. Until recently, the flow of knowledge between biology and robotics was unidirectional, from biology to robotics. During the last decade a bi-directional link has been established between biology and robotics based on the realization that life-like machines provide a wonderful platform to quantitatively test and analyze the computational models and theories from neuroscience [13, 32], psychology, developmental study [33], and human locomotion [34, 35]. As mentioned in [36], the bio-inspired robots act as the '*mirror to reflect our humanity back at us as we interact with them*'.

Designing a robot with human-like sophistication in structure and intelligence is a cross-disciplinary endeavor and requires intense collaboration among disciplines such as biology, neuroscience, psychology, linguistics, robotics and AI. The efforts made in this endeavor can be categorized into four distinct categories.

- **Biomimetic perception:** Perception is the key requirement for survival of the living elements [37]. The pre-requisites of primates- like reasoning and decision making is to have primates- like perception. The perceptual system, therefore, is one of the most significant aspects of bio-inspired robot design. There is a steady progress in the development of biomimetic sensors and actuators technology. Such sensors and actuators enable a robot to perceive and interact with the environment in primates-like fashion (more specifically, human like). In other words, biomimetic sensors and actuators help the robots to perceive the same representation of the world as human does and thereby ease the blending of robots in the human environment. The log-polar camera for human like vision [38], haptic devices to mimic touch sensitivity [39], micro electro-mechanical systems (MEMS)[40] and elector-active polymer (EAP) to model the biological muscles [41] are among the many examples of biomimetic sensors and actuators. The possibility of integrating soft tissue to construct flexible and deformable robots are on the way to become full-fledge areas of research and applications [42]. A large group of robotics researchers are currently working on reverse engineering the performance characteristics of biological sensors to formalize control mechanisms of biomimetic sensors as well as their power requirements and efficiency.
- **Locomotion and control:** Locomotion of autonomous robots based on the motion primitives or imitation of biological creatures is a rapidly emerging research area in bio-inspired robotics. The major focus is to mimic lower level sensory-motor

skills of biological creatures (ranging from insect to human) in autonomous robots. Bipedal walking by humanoid robots [43, 44], humanoid upper body control [45, 46], design and control of articulated robots e.g. reconfigurable robots [47, 48], crawling and jumping robots [49, 50, 51] are only a few examples of widespread research in bio-inspired locomotion control in robotics.

- **Control architectures and learning methodologies:** These are the sub-discipl-ines of bio-inspired robotics which have been using bio-inspired mechanisms for a long period of time. Majority of the existing control architectures used in autonomous robotics are bio-inspired. The traditional reactive [52], deliberative, and hybrid [53] controllers are inspired from insect locomotion control mechanism whereas the relatively newer behavior-based controller [54] obtains inspiration from human cognition. Similarly, the learning methodologies commonly used in robotic, e.g. reinforcement learning, associative learning, classical conditioning, automated animal like (AA)-learning [55], neural network and statistical learning, are designed based on the learning process of biological creatures ranging from insect to human.
- **Cognitive modeling:** Cognitive modeling deals with implanting human-like cognition, albeit reduced complexity, in autonomous robots with the hope that the cognitive capacities, as they work in human and other biological creatures, will also assist the new generation robots to be coherent, self-motivated, social, persistent in behavior, and aware of themselves and their environments. Cognitive modeling, therefore, requires integration of neuroanatomy, cognitive neuroscience, cognitive psychology, developmental study, linguistics, and AI with robotics. A rapidly increasing number of publications on different aspects of cognitive modeling indicates the growing interest in this research area, although a complete model of robot cognition does not yet exist [56, 57]. The latest findings of neuroscience and psychology are continuously modulating the research on cognitive modeling for autonomous robots. Apart from few general theories on robot cognition (e.g. [9, 46, 58, 59, 60, 61]), the majority of the literature is focused on developing models for discrete cognitive abilities, e.g. attention, learning, value system, reasoning, and decision making. The research on cognitive modeling for autonomous robots, therefore, is still in its infancy and there is a long way to traverse before having a full fledge autonomous robot with human-like cognition.

A large number of university research laboratories around the globe is performing research on different areas of bio-inspired robotics: the biologically inspired robotics group at Ecole Polytechnique, the biorobotics laboratories at Harvard University, University of Washington, and MIT, the cognitive robotics labs at Vanderbilt University, Technical University of Munich, University of Genova, Michigan State University, University of Southern California, and Idaho National Laboratory. A growing number of conferences (e.g. EpiRob, ICDL) and journals (e.g. International Journal of Humanoid Robotics, special issues on bio-robotics of the IEEE Transaction on Robotics and Connection Science) are now fully dedicated to the findings from bio-inspired robotic research.

The rest of this chapter focuses on the emerging use of CI techniques in cognitive modeling for autonomous robots. It provides a survey on the state-of-the-art of cognitive modeling in pursuit of human-like intelligent machine and investigates on how the CI tools have been invoked in modeling different aspects of cognition. It also advocates the idea that the features of cognition emerges naturally in CI techniques, when properly utilized. The CI tools, therefore, offer a very convenient way to model artificial cognition in autonomous robots.

1.4 Cognitive Modeling for Autonomous Robots: CI-Based Approaches

With the tremendous advancement of computer systems, both in speed and storage capacity, AI has achieved significant strides during the past decades. Several AI techniques have emerged as a consequence of the enriched computational power. The advancements in AI robotics, to a large extent, is the consequence of this enriched computational power. However, today's computers with their enormous speed and storage capacity essentially act as *mindless intelligence*, executing complex routines with extreme efficiency but showing minimal awareness about the tasks they are performing. AI researchers, therefore, have started working on developing cognitive computers which will be able to learn from its experience and apply the learned knowledge to deal with anomalies [62]. Initiatives taken by AI robotics researchers are one step ahead of this effort. Their idea is to develop embodied physical agents namely, cognitive robots, which are expected to act, behave, and think like humans while interacting with natural human environments. In pursuit of such an ideal goal, the only target device to mimic has always been the human brain. With the advent of new technologies, such as fMRI (functional Magnetic Resonance Imaging) [63], PET (Positron Emission Tomography) [64], neuroscience has been experiencing a significant forward shift toward a better understanding of human brain, yet major part of it is still unknown [37]. The advancements in neuroscience have introduced a remarkable change in the perception of the psychologists about human cognition and have encouraged the thought of explaining cognitive developments in terms of the changes in physical structure of the brain [65, 66, 67, 68].

1.4.1 Cognition: Robot and Human

Since antiquity cognition has been a major research area in psychology and philosophy. It is probably one of the areas where modern neuroscience and psychology have performed the most significant improvement, although there is still a lot more to know [37, 68]. Elucidating cognition in a precise manner is difficult, yet all of us are generally aware of our cognitive abilities. In simple words, 'cognition' of a living element refers to its capacity to process perceptual information and thereby manipulating its behavior. Human cognition encompasses a large collection of processes occurring in human mind. The cognitive capabilities of humans are generally manifested in the following [10, 11, 37, 66, 67, 68].

- Self awareness,
- perception,
- learning,
- knowledge,

- reasoning,
- planning and decision making.

Generally, action execution is not considered as a part of cognition, although cognitive development is largely influenced by our capability to act upon the environment. Besides, action is the only explicit means onto which we reflect our cognitive skills. Designing an artificial agent with some or all of these powerful capabilities is the new grand challenge of AI [30, 62]. A number of attempts have been made over the past few years to meet this challenge and gave birth to a number of new research areas including ‘developmental engineering’ [46], ‘epigenetic robotics’ [69], ‘developmental robotics’ [58], and ‘developmental cognitive robotics’ [60]. All of them share the common vision of designing human-like cognitive agents, irrespective of their names and the methodologies applied. This chapter addresses these ‘similar vision’ efforts as ‘cognitive modeling for autonomous robots’.

Based on the recent neuro-biological and psycho-physical findings about executive cognitive functions of human being (e.g. attention, learning, perception, social

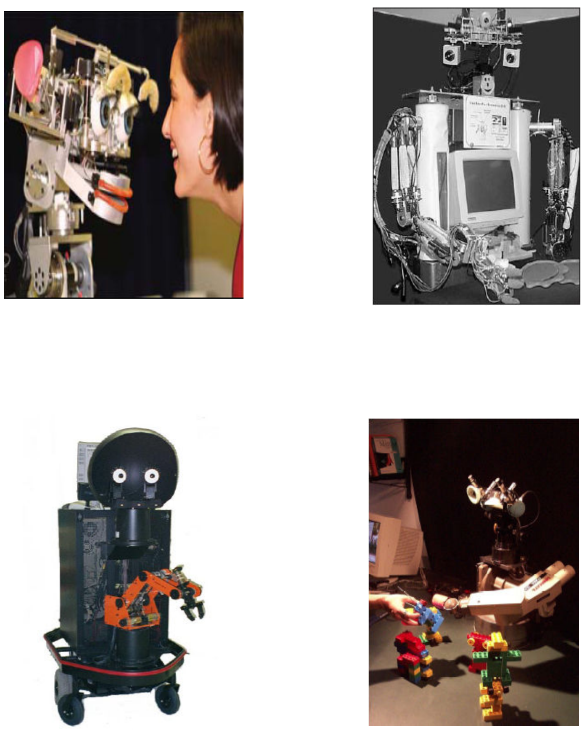

Fig. 1.1. Example robotic systems based on bio- inspired cognitive models (a) Kismet (MIT), (b) ISAC (Vanderbilt University), (c) SAIL robot (Michigan University) (d) Babybot (University of Genova)

communication), an impressive amount of research work has been carried out during the current decade in the following sectors of cognitive modeling:

1. Value system
2. Visual attention
3. Social cognition

The rest of this chapter will provide a brief survey on the state-of-the-art of each of these sectors of cognitive modeling. Two criteria have been defined for a research work to be included in the survey presented in this chapter.

- The research has to apply computational intelligence (CI) techniques to deal with the problem in the associated research area.
- The research has to demonstrate the performance of the designed intelligence framework using any physical robotic system.

The representative works in different sectors of cognitive modeling (value system, visual attention, and social cognition) are summarized and presented in tabular form for convenience in comparison.

1.4.2 Value System

The value system refers to the capacity of a biological brain to increase the likelihood of neural response to an external phenomena provided that there exists a prior experience of having the similar phenomena [70]. The combined action of internal perception, reasoning and decision making capacity contributes in development of values in the primates. Value is not hard-wired in human since birth, rather it grows developmentally while mediated by the plasticity of human brain [10, 11, 37]. Accordingly, the value with which a biological entity is born with is termed as 'innate value' whereas the value that it achieves through experience during the course of development is called 'acquired value'. The plasticity of human brain, which makes the development of acquired value possible, is a recent discovery in neuroscience. The acquired value of a biological entity is reflected in its behavioral adaptivity. The robotic counterpart of value refers to the capacity of an autonomous robot to plan action upon detection of salient stimuli. A robot with value system performs this action planning after analyzing its internal and external context [13, 71]. Internal context of a robot is the knowledge-base developed through past experiences whereas external context refers to the current environmental situation in favor of a planned action. A value-based robot, therefore, is aware of its own action.

Value system is a crucial requirement of developing human-like intelligence in robotic systems. The success of designing truly developmental robot depends largely on the design of a value system. The basic idea of the artificial value system for autonomous robots is to design a mechanism which can reflect the effect of the past experience in the future behaviors (e.g. in planning of specific action, perceptual categorization, conditioning, autonomous exploration) of the robots. Artificial value system essentially tries to modulate the behavior of an autonomous system (e.g Fig. 1.2 shows the modulating effect of value system in the SAIL robot cognitive architecture [72]).

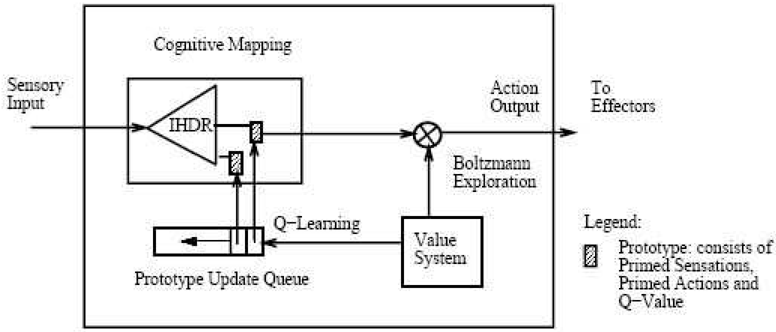

Fig. 1.2. Modulating role of value system in the cognitive architecture of SAIL robot in university of Michigan (adapted from [72])

Considering value system in the primates as benchmark [73, 74], the properties expected in an artificial value system for the autonomous robots can be summarized as follows.

- Prediction: Predictive power is an important requirement of a value system. The system should be able to infer the consequences of its own action before actually executing it. This sort of predictive action planning requires the capacity to apply reasoning and knowledge-base to analyze perceptual information.
- Task non-specific: An artificial value system must be general and should operate in a task non-specific manner. It must be unsupervised and should enable a robot to learn by itself (from the consequence of its action) without any help from human instructor. Instructional scaffolding is a very popular mechanism in the primates (specially, human being) to boost value system development during the very early stage but the supervision obtained through scaffolding is expected to be decayed gradually in order to facilitate the natural cognitive development [80]. In a similar manner, limited support is allowed during the early development of artificial value system in robotic agents but, gradually, the system should be capable of evolving in a an autonomous manner based on the interaction with its environments.
- Developmental: Similar to the value system in biological entity, the artificial value system might have innate and acquired components. Innate value, in artificial systems, is modeled through assigning prior determined importance to different actions. The acquired value, on the other hand, should generate developmentally. An artificial value system must have the plasticity to continuously encode the feedback that it receives from its interaction with environment. This encoding of experience should be in such a way that facilitate emergence of adaptive behavior.
- Value-based Learning: Learning is the prime mechanism which get modulated through the activities of value system. An artificial values system, therefore, should be capable of generating modulating signals to adapt various learning parameters, e.g bias (positive or negative), learning rate.

Table 1.1. Research on artificial value system for autonomous robots

Lead research	Synopsis	CI technique	Robot
Value system [13]	Development of a neuromodulatory system based on conditioning and categorization	NN (continuous) firing rate model	Khepera (Monad)
Value system for developmental robot [71, 72, 75]	Development of motivation and action planning through value system	Q-learning	HR (SAIL robot)
Intelligent Adaptive Curiosity [76, 77]	Intrinsic motivation generation for action planning	NN or any standard learning algorithm	PR (AIBO)
Adaptive behavior [78]	Development of a self-modulating value system	NN	MR (DARWIN V)
Value system for categorization [79]	Value guided exploration and perceptual categorization	NN	Khepera
PR: Pet Robot	MR: Mobile Robot	HR: Humanoid Robot	

Table 1.1 summarizes the research on value system design in autonomous robots. The initial attempts to design artificial value system were made by a group of researchers using robotic systems as a testbed to simulate the theories of primates nervous system [59, 81, 82, 83]. The efforts on designing artificial value system with the goal of developing human-like intelligence in robotic systems, however, are very limited. With the advancement of developmental robotics, the value system design for autonomous robot is gradually gaining attention of the bio-inspired robotics researchers [13, 71, 72, 75, 76, 77, 78, 79].

Artificial Neural networks generally dominate as a design tool in the development of artificial value system. The reason behind this, partly, is our current understanding about the operation of the primates value system. The findings on developmental plasticity suggest that experience drastically changes the ease with which neurons interact with each other [10, 11, 37]. The architecture of artificial neural networks provides a suitable way to model this synaptic modulation as adaptive weight adjustment among connecting neural processing elements.

1.4.3 Visual Attention

Attention, in a biological system, refers to the process of selecting a set of relevant information for further processing. It plays a key role in the survival and normal operation of the biological entities as the gate-keeping activity of attention saves the information processing unit (generally the brain) from being flooded with enormous amount of information. Computational modeling of the primates attention mechanism (more accurately, visual attention mechanism) has become a very popular research area in the recent years due to it potential applications in computational neuroscience, computer vision, automated video surveillance, and AI robotics.

The purpose of attention mechanism, when applied on the artificial systems, is essentially the same as that in the biological systems: focusing on behaviorally relevant information for further processing. A properly designed attention system provides a task-executing robot with the capacity to blend with human in natural human environment.

Extensive research has been performed on the visual attention mechanism of the primates, both in psychology [65, 68, 84, 85, 86, 87, 88, 89] and neurobiology [90, 91, 92, 93, 94, 95]. Based on these research a good number of bio-inspired computational model of visual attention has been proposed in computer vision [96, 97, 98, 99, 100, 101, 102, 103, 104] and in computational neuroscience [105, 106, 107, 108, 109]. The models in computer vision mostly focus on the technical aspects of the attentional mechanism while the goal of the models in computational neuroscience is to simulate the findings from the primates behavioral data. In the recent years, with the emergence of bio-inspired robotics, the robotic researches have started working on developing artificial attention mechanism for embodied physical robots. Accordingly, a number of attention models has been proposed in robotics literature which are dealing with embedding artificial attention mechanism in robotic systems [103, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121]. This chapter categorizes the existing literature on visual attention into three different groups.

- Theoretical model for visual attention: This group includes the theoretical models of visual attention which are based on CI technique and have been implemented in robotic systems for attention modeling. The most notable work in this category is the neuromorphic vision tool-kit (NVT) [99, 122](Fig. 1.3). NVT is an extension of the first computational model of visual attention proposed in [97]. It uses winner-take-all type neural network (WTA-NN) for selective attention modeling. The WTA NN have earned huge popularity in the later years and is a key tool for attention modeling in majority of the existing visual attention models, although it has been considerably modified from its original form as proposed in [97]. A good number of works in robotics uses different variants of WTA NN and NVT to implement visual attention [111, 113, 123, 124, 125].
- Robotic model of visual attention: The visual attention models developed specifically for robotic systems are included in this category [111, 116, 126, 127, 128, 129, 130]. A considerable number of model in this category are based on NVT and WTA-NN. Apart from that, competitive NN, radial basis function (RBF), self organizing map (SOM), arrays of neural processing elements (PE) are popular CI tools used for visual attention modeling.

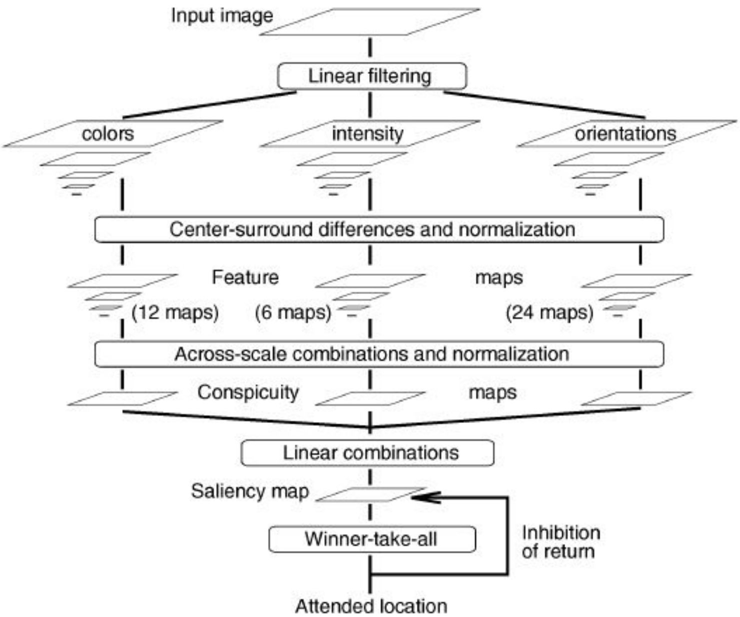

Fig. 1.3. Neuromorphic vision toolkit: an architecture of visual attention mechanism (adapted from [99])

- Task specific visual attention model: Focusing attention on an object of interest is the pre-requisite of learning skill development. A substantial number of robotic system, therefore, use visual attention as the basic mechanism to achieve different cognitive skills. These systems generally develop task-specific models of visual attention where the task in hand might be object manipulation [131, 132, 133, 134], different forms of human robot interaction (HRI) [61, 135, 136, 137, 138, 139], and robot navigation [125].

For quick reference, tables 1.2, 1.3, and 1.4 summarize the leading researches under each of the above mentioned categories, respectively. The existing models of visual attention have achieved significant success addressing the issues of 'what to attend', 'when to attend', and 'how to attend'[103].

The majority of the visual attention models for the autonomous robots use different kind of artificial neural networks. The reason behind this, partly, is that the earlier computational models of visual attention were NN-based. The another reason is that the enriched formulation of artificial neurons act as a very strong tool to mimic (albeit reduced complexity) the neural circuity of visual cortex dedicated to attention selection. As the goal of bio-inspired robotics is to mimic the functionality of biological system rather than the exact mechanism, there are possibilities for other computational techniques to be used in developing visual attention models. For instance, fuzzy reasoning could play a substantial role in visual search modeling because of its tolerance

Table 1.2. Theoretical models of visual attention

Lead research	Synopsis	CI technique
Adaptive Resonance theory [96]	A neural network based on attention mechanism. Combines top-down and bottom -up attention	Neural network
Koch's Model [98], Neuromorphic vision tool-kit (NVT) [99, 122]	Computational model of visual attention. Implements saliency map and inhibition of return (IOR)	Winner-take-all neural network (WTA NN)
Selective tuning model [101]	Conncectionist model of visual attention	Neural network
Feature-gate model [102]	Conncectionist model of visual attention. Combines feature integration theory [84] and guided search [85]	Spatially distributed, hierarchical neural network

to partial truth [56]. Further, statistical learning methodologies offer great versatility in the learning of attention based cognitive skill. Specifically the probabilistic architecture provides the most suitable way to handle the perceptual and decision uncertainty inherent in robotics applications. We have not yet found a general purpose model of visual attention capable to tackle all the existing challenges. Integration of different CI techniques might be a very intriguing way to walk toward this goal since it may capture different functionalities that can not be handled by an isolated CI or AI approach.

1.4.4 Social Cognition

Social cognition development in autonomous systems is a widely explored research area in bio-robotics. The research on socially interactive robots has been experiencing a steady development since the birth of biologically inspired robotics. A number of significant achievements have been made, but researchers are interested about very high-level social interaction conducted by robotic agents. A number of different classifications and taxonomies are available for socially interactive robots ([33, 36, 158, 159] are suitable for extensive survey). This document focuses on the body of research dedicated to design task non-specific social cognition in robotic agents as a part of fulfilling the goal of designing human-like cognition in robotic systems. Such research works generally involve the theories of social development of the human proposed in psychology, ethology, linguistics, neuroscience and developmental cognitive neuroscience. The target robotic systems for these approaches may possess physical embodiment but

Table 1.3. Robotic model of visual attention

Lead research	Synopsis	CI technique	Robot
Distributed attention [113]	Multi-processor attention model	WTA NN (Koch's model)	7 DOF HH
Object-based attention [111]	Considers object as elemental unit for attention. Evaluates object-based saliency map.	WTA NN (NVT)	HR (Babybot)
Attention network [140]	Efficient visual search by robotic system	Neural network (Feature gate model)	CH
Overt attention [110]	Implements space -based saccade and IOR	Competitive NN [141]	HR
Attention and saccade generation [123]	Implements space -based saccade	WTA NN (Koch's model)	CH
Autonomous mental development (AMD) [58, 142] [143, 144, 145]	A developmental design of visual attention mediated by subsumption [54]	Hierarchically connected neural processing elements (PE)	HR (SAIL robot)
NeuroBotic system [116, 126, 127, 128]	Object classifier based on task-relevance	Hierarchical radial basis function (RBF)	MR (Peoplebot)
MirrorBot project [129, 130]	A distributed model of spatial attention	Continuum neural field theory	MR (peoplebot)
Multi modal attention [146, 147]	Directing visual attention to respond stimuli arising through different modality	NN	CRA
Brain based devices [32, 59] [148]	Attention-based perceptual categorization and visual binding	network of mean firing-rate neurons	MR (Darwin VII)
HH: Humanoid Head	HR: Humanoid Robot	CH: Camera Head	CRA: Camera on Robot Arm

Table 1.4. Task-specific model of visual attention

Lead research	Synopsis	CI technique	Robot
Attention for manipulation and reasoning [131]	visual attention helps to perform manipulation task and plan task activities	Coupled dynamic neural field	MR
Attention guided object manipulation by robotic hand [132]	visual attention mechanism help a robot to focus on target object for grasping task	NN	CH
Visual attention for mobile robots [133, 134]	A connectionist attention model for task executing robots	Spiking and mean firing-rate neurons (selective tuning model)	MR (Khepera)
Attention guided robot navigation [125]	attention mechanism is used to calculate the orientation of a robotic system	WTA NN and RBF NN	MR
Intelligent machine architecture for HRI [61, 135] [136, 137]	RBF associated with sensory egosphere implements visual attention	NN	HR (ISAC)

not necessarily human-like morphology or face, although these two have been proved to facilitate the social interaction between robots and humans. This type of socially interactive robot has been termed in the literature as 'sociable robot' [159].

The studies in psychology and neuroscience on social cognition development in humans identify the active interaction with other human as well as with the environment as the key criteria of social cognition development in human child [10, 80, 160]. The AI robotics research on social cognition development in autonomous systems, therefore, is primarily focusing on developing mechanisms used by the robots to interact with humans. The efforts in this area can be categorized into the following two groups.

- **Joint attention:** Shared or joint attention refers to the ability to intentionally attend to an object/region of mutual interest. This is the ability that human infants start to achieve as early as six months [161]. Joint attention is an extremely complex process demanding the capacity to understand other peoples perspective and intention. It is a fundamental requirement for developing social cognition. An impressive body

Table 1.5. Research on joint visual attention

Lead research	Synopsis	CI technique	Robot
Active learning of Joint attention [149, 150]	Learning joint attention through pointing and reaching by robots	RBF NN	HR (NICO)
Learning joint attention [151, 152, 153]	Passive learning of joint attention through bootstrap mechanism	Multilayer NN, Q-learning	HH
Attention for social communication [124, 154] [155, 156]	Joint attention between human and robots based on eye contact	WTA NN (NVT)	HH (Kismet)
Join attention learning for HRI [138, 139]	Joint attention between human and robots based on gaze following	Self organizing map (SOM)	MR
Joint attention for imitation [157]	Imitation is achieved through joint attention	Recurrent NN (RNN)	HR (Sony QRIO)

of research work has been reported in the past few years on developing the joint attention capability in robotic systems. Table 1.5 provides a brief summary of the research on joint attention. Gaze following technique has been used in a number of works to identify the intent of the partner in a social engagement [124, 138, 139, 154, 155, 156]. Using the embodiment of the robots to attract the attention of partner (e.g. through pointing fingers or waving hand) is another popular way of achieving joint attention [149, 150].

- **Social imitation:** Learning through imitation has gained much popularity in bio-inspired robotics. Imitation provides a powerful way of developing social behavior. More specifically, the sensori-motor skills required to generate different types of social cues (e.g. pointing, reaching, waving) and task sequence learning are the two major areas where imitation based interaction between humans and robots plays a very significant role. The success of imitation based learning, however, depends on the integration with other cognitive abilities of a robotic system, e.g. attention, values system. The task of skilled imitation, therefore, has been termed as a 'hard problem' in [162] subjected to the issues '*what to imitate*', '*when to imitate*', '*how to imitate*', and '*what is the evaluation criteria of imitation*'. Table 1.6 presents a brief summary of research on imitation based learning as a means of developing social cognition in autonomous robots.

Table 1.6. Research on social imitation

Lead research	Synopsis	CI technique	Robot
Imitation learning [163]	Motion sequence generated by a human teacher to perform simple tasks are observed and imitated	Bayesian learning, Hidden Markov model (HMM)	HR (Fujitsu HOAP-2)
Learning motor skills through imitation [164]	A training phase trains the robot with different motor skills. The robot imitate learned skills in future engagements	RNN	HR (Sony QRIO)
Imitation behavior [165]	Attention guided imitation of hand posture	Reinforcement learning, HMM	HR (Kenta)
Learning through demonstration [166, 167]	Manipulation task is learned through imitating the task sequence executed by a human teacher	HMM, probabilistic analysis	HR (HOAP-2)
Early imitation ability [168]	Developmental approach of imitation. Learning imitation through self exploration	NN, causal learning	HR (H3)
Gaze shift learning by imitation [169]	Learning of gaze shifting inspired by saliency through imitating caregiver	HMM	MR (Pioneer)
Learning by imitation [170, 171]	Architecture for learning motion primitives through viewpoint transformation and visuo-motor mapping	NN	HR

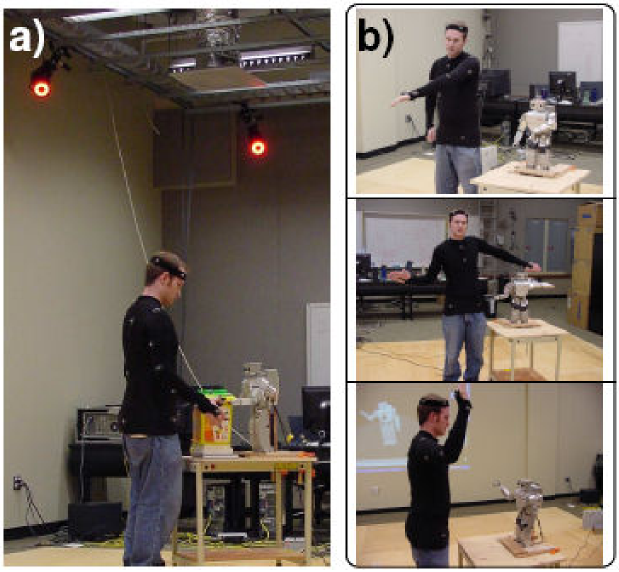

Fig. 1.4. The humanoid robot HOAP-2 engaged in an imitation task (adapted from [163])

Similar to value system and visual attention, the research on social cognition is influenced by different types of artificial neural networks [164, 170, 171], although probability-based algorithms have earned much popularity in the design of social imitation capacity [163, 165, 166, 167, 169].

1.5 Conclusion

The ultimate goal of bio-inspired robotics is to build human-like machine, in terms of morphology as well as functionality. The solemn purpose of developing human-like machine is the hope that their human-like intelligence will help them to blend naturally with humans and be a great assistance in human's everyday operations. For instance, intelligent life-like machines will tremendously improve the quality of human life through their assistance in industry, health care, search and rescue, cleaning and household works, space-operation, education and entertainment. Design of human-like machine remains a challenge for the next generation autonomous robotics. Mimicking the mechanism of intelligence development in the biological creatures (specially in human) is currently seen to be a better option in resolving this challenge as compared to the earlier efforts of 'hand-coding' the intelligence in machines. In this endeavor one important issue, as mentioned in [172], is mimicking the intelligent behavior of a biological creatures does not guarantee an automatic emergence of intelligence in a target machine. Rather we have to find the underlying principle that governs the emergence of intelligent behavior. Mimicking the principle, rather than the outcome, might lead us to our goal of designing life-like machine. At this point, the CI techniques show us a relatively better hope. Majority of the CI techniques are developed based on different elegant aspects of the biological creatures, e.g. morphological structure, thinking process, evolutionary selection. The CI techniques, therefore, blend naturally with the goal of bio-inspired robotics.

This chapter have summarized some efforts to reach the goal of designing human-like machine mediated by different CI techniques. The major focus was on the research on cognitive modeling for autonomous robots. Majority of the research in cognitive modeling is intended to model the small pieces of cognition, e.g. attention, value system, social interaction. Different kind of neural networks have gained more popularity and acceptability in this endeavor as compared to the other CI tools, e.g. fuzzy reasoning, genetic algorithm and probabilistic reasoning. The integration of neural network with other powerful CI tools might improve the scenario significantly, although such efforts are still in the early stages. After designing the small pieces of cognition, the most crucial part is to integrate them in a single architecture and have them interact with each other in a meaningful way so that we can see human-like manifestations of cognition as their integrated outcome. Such an architecture is yet to be developed but we hope that the CI techniques will contribute in its design, the same way they have been contributing in modeling the discrete cognitive abilities of autonomous robots.

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