Cognitive System

David Vernon,
Institute for Cognitive Systems
Technische Universität München, Germany

Synonyms

– Cognitive Agent

Related Concepts

– Artificial Intelligence
– Cognitive Architecture
– Cognitive Vision

Definition

A cognitive system is an autonomous system that can perceive its environment, learn from experience, anticipate the outcome of events, act to pursue goals, and adapt to changing circumstances.

Background

There are several scientific perspectives on the nature of cognition and on how it should be modelled. All fall under the general umbrella of cognitive science which embraces the disciplines of neuroscience, artificial intelligence, cognitive psychology, linguistics, and epistemology. Among these differing perspectives, however, there are two broad classes: the *cognitivist* approach based on symbolic information processing representational systems, and the *emergent systems* approach, encompassing connectionist systems, dynamical systems, and enactive systems, all based to a lesser or greater extent on principles of self-organization [1,2,3,4]. A third class — *hybrid systems* — attempts to combine something from each of the cognitivist and emergent paradigms. All three approaches have their origins in cybernetics [5] which in the decade from 1943 to 1953 made the first efforts to formalize what had up to that point been purely psychological and philosophical treatments of cognition. The intention of the early cyberneticians was to create a science of mind, based on logic. Examples of the application of cybernetics to cognition include the seminal paper by McCulloch and Pitts 'A logical calculus immanent in nervous activity' [6] and Ashby's 'Design for a Brain' [7].

Theory

The initial attempt in cybernetics to create a science of cognition was followed by the development of an approach referred to as *cognitivism*. The birth of the cognitivist paradigm, and its sister discipline of Artificial Intelligence, dates from a conference held at Dartmouth College, New Hampshire, in July and August 1956 and attended by people such as John McCarthy, Marvin Minsky, Allen Newell, Herbert Simon, and Claude Shannon. Cognitivism holds that cognition is achieved by computation performed on internal symbolic knowledge representations in a process whereby information about the world is abstracted by perception, and represented using some appropriate symbolic data-structure, reasoned about, and then used to plan and act in the world. The approach has also been labelled by many as the information processing or symbol manipulation approach to cognition [1,8,9,10]. In most cognitivist approaches concerned with the creation of artificial cognitive systems, the symbolic representations are the descriptive product of a human designer. This is significant because it means that they can be directly accessed and interpreted by humans and that semantic knowledge can be embedded directly into and extracted directly from the system. In cognitivism, the goal of cognition is to reason symbolically about these representations in order to effect the required adaptive, anticipatory, goal-directed behaviour. Typically, this approach to cognition will deploy machine learning and probabilistic modelling in an attempt to deal with the inherently uncertain, time-varying, and incomplete nature of the sensory data that is used to drive this representational framework. Significantly, in the cognitivist paradigm, the instantiation of the computational model of cognition is inconsequential: any physical platform that supports the performance of the required symbolic computations will suffice [8]. This principled separation of operation from instantiation is referred to as functionalism.

In the emergent paradigm, cognition is the process whereby an autonomous system becomes viable and effective in its environment. It does so through a process of self-organization by which the system continually maintains its operational identity through the moderation of mutual system-environment interaction. In other words, the ultimate goal of an emergent cognitive system is to maintain its own autonomy. In achieving this, the cognitive process determines what is real and meaningful for the system: the system constructs its reality — its world and the meaning of its perceptions and actions — as a result of its operation in that world. Consequently, the system's understanding of its world is inherently specific to the form of the system's embodiment and is dependent on the system's history of interactions, i.e., its experiences. This mutual-specification of the system's reality by the system and its environment is referred to as co-determination [11] and is related to the concept of radical constructivism [12]. This process of making sense of its environmental interactions is one of the foundations of the enactive approach to cognition [13]. Cognition is also the means by which the system compensates for the immediate nature of perception, allowing it to anticipate environmental interaction that occurs over longer timescales. That is, cognition is intrinsically linked with the ability of an agent to act prospectively: to deal with what might be, not just with what is. Many emergent approaches adhere to the principle that the primary model for cognitive learning is anticipative skill construction rather than knowledge acquisition. Thus, processes which guide action and improve the capacity to guide action form the root capacity of all intelligent systems [14].

As noted already, the emergent paradigm embraces connectionist systems, dynamical systems, and enactive systems. Connectionist systems rely on parallel processing of non-symbolic distributed activation patterns using statistical properties, rather than logical rules, to process information and achieve effective behaviour [15]. In this sense, the neural network instantiations of the connectionist model are dynamical systems that capture the statistical regularities in training data [16]. Dynamical systems theory has been used to complement classical approaches in artificial intelligence [17] and it has also been deployed to model natural and artificial cognitive systems [10,18,19]. Although dynamical systems theory approaches often differ from connectionist systems on several fronts, it is better perhaps to consider them complementary ways of describing cognitive systems, dynamical systems addressing macroscopic behaviour at an emergent level and connectionist systems addressing microscopic behaviour at a mechanistic level [20]. Enactive systems take the emergent paradigm even further. Enaction [13,21,22,23] asserts that cognition is a process whereby the issues that are important for the continued existence of a cognitive entity are brought out or enacted: co-determined by the entity and the environment in which it is embedded. Thus, enaction entails that a cognitive system operates autonomously, that it generates its own models of how the world works, and that the purpose of these models is to preserve the system's autonomy.

Considerable effort has gone into developing hybrid approaches which combine aspects of cognitivist and emergent systems. Typically, hybrid systems exploit symbolic knowledge to represent the agent's world and logical rule-based systems to reason about this knowledge in order to achieve goals and select actions, while at the same time using emergent models of perception and action to explore the world and construct this knowledge. Thus, hybrid systems still use cognitivist representations and representational invariances but they are constructed by the system itself as it interacts with and explores the world rather than through a priori specification or programming. Consequently, as with emergent systems, the agent's ability to understand the external world is dependent on its ability to interact flexibly with it and interaction is the organizing mechanism that establishes the association between perception and action.

Cognitivism and artificial intelligence research are strongly related. In particular, Newell's and Simon's 'Physical Symbol System' approach to artificial intelligence [8] has been extremely influential in shaping how we think about intelligence, natural as well as computational. In their 1976 paper, two hypotheses are presented: the *Physical Symbol System Hypothesis* and the *Heuristic Search Hypothesis*. The first hypothesis is that a physical symbol system has the necessary and sufficient means for general intelligent action. This implies that any system that exhibits general intelligence is a physical symbol system *and* any physical symbol system of sufficient size can be configured to exhibit general intelligence. The second hypothesis states that the solutions to problems are represented as symbol structures and that a physical-symbol system exercises its intelligence in problem-solving by search, that is, by generating and progressively modifying symbol structures in an effective and efficient manner until it produces a solution structure. This amounts to an assertion that symbol systems solve problems by heuristic search, *i.e.* the successive generation of potential solution structures. The task of intelligence, then, is is to avert the ever-present threat of the exponential explosion of search. Subsequently, Newell defined intelligence as the degree to which a system approximates the ideal of a knowledge-level system [24]. A knowledge-level system is one which can bring to bear *all* its knowledge onto *every* problem it attempts to solve (or, equivalently, every goal it attempts to achieve). Perfect intelligence implies complete utilization of knowledge. It brings this knowledge to bear according to the *principle of maximum rationality* which was proposed by Newell in 1982 [25] as follows: 'If an agent has knowledge that one of its actions will lead to one of its goals, then the agent will select that action'. Anderson [26] later offered a slightly different principle, the *principle of rationality*, sometimes referred to as rational analysis, stated as follows: 'the cognitive system optimizes the adaptation of the behaviour of the organism'. Note that Anderson's principle considers optimality to be necessary for rationality, something that Newell's principle doesn't.

Cognitivist and emergent approaches are normally contrasted on the basis of the symbolic or non-symbolic nature of their computational operation and representational framework. Cognitivist systems typically use production systems to effect rule-based manipulation of symbol tokens whereas emergent systems exploit dynamical processes of self-organization in which representations are encoded in global system states. However, the distinction between cognitivist and emergent is not restricted to the issue of symbolic representation and they can be contrasted on the basis of several other characteristics such as semantic grounding, temporal constraints, inter-agent epistemology, embodiment, perception, action, anticipation, adaptation, motivation, autonomy, among others [27].

The differences between the cognitivist and the emergent paradigm can be traced to their underlying distinct philosophies [28]. Broadly speaking, cognitivism is dualist, functionalist, and positivist. It is dualist in the sense that there is a fundamental distinction between the mind (the computational processes) and the body (the computational infrastructure and, if required, the physical structure that instantiates any physical interaction). It is functionalist in the sense that the actual instantiation and computational infrastructure is inconsequential: any instantiation that supports the symbolic processing is sufficient. It is positivist in the sense that they assert a unique and absolute empirically-accessible external reality that is apprended by the senses and reasoned about by the cognitive processes. In contrast, emergent systems are neither dualist nor functionalist, since the system's embodiment is an intrinsic component of the cognitive process, nor positivist, since the form and meaning of the system's world is dependent in part on the system itself. The emergent paradigm, and especially the enactive approach, can trace its roots to the philosophy of phenomenology [28,29].

A criticism often levelled at cognitivist systems is that they are relatively poor at functioning effectively outside well-defined problem domains because they tend to depend on in-built assumptions and embedded knowledge arising from design decisions. Emergent systems should in theory be much less brittle because they develop through mutual specification and co-determination with the environment. However, the ability to build artificial cognitive systems based on emergent principles is very limited at present and cognitivist and hybrid systems currently have more advanced capabilities within a narrower application domain.

Any cognitive system is inevitably going to be complex. Nonetheless, it is also the case that it will exhibit some degree of structure. This structure is often encapsulated in what is known as a cognitive architecture [30]. Although used freely by proponents of the cognitivist, emergent, and hybrid approaches to cognitive systems, the term cognitive architecture originated with the seminal cognitivist work of Newell et al. [25]. Consequently, the term has a very specific meaning in this paradigm where cognitive architectures represent attempts to create unified theories of cognition [24,31], i.e. theories that cover a broad range of cognitive issues, such as attention, memory, problem solving, decision making, learning, from several aspects including psychology, neuroscience, and computer science. In the cognitivist paradigm, the focus of a cognitive architecture is on the aspects of cognition that are constant over time and that are independent of the task. Since cognitive architectures represent the fixed part of cognition, they cannot accomplish anything in their own right and need to be provided with or acquire knowledge to perform any given task. For emergent approaches to cognition, which focus on development from a primitive state to a fully cognitive state over the life-time of the system, the architecture of the system is equivalent to its phylogenetic configuration: the initial state from which it subsequently develops through ontogenesis.

Open Problems

The study of cognitive systems is a maturing discipline with contrasting approaches. Consequently, there are several open problems. These include the role of physical embodiment, the need for development, the system's cognitive architecture, the degree of autonomy required, the issue of symbol grounding, the problem of goal specification, the ability to explain the rationale for selection actions, the problem of generating generalized concepts and transferring knowledge from on context to another, and the interdependence of perception and action. The nature of any resolution of these problems is inextricably linked to the choice of paradigm: cognitivist, emergent, or hybrid.

The role of physical embodiment in a cognitive system [32,33,34] depends strongly on the chosen paradigm. Due to their functionalist characteristics, cognitivist systems do not depend on physical embodiment to operate successfully but there is nothing to prevent them from being embodied if that is what the task in hand requires. Emergent systems, by definition, require embodiment since the body plays a key role in the way a cognitive system comes to understand — make sense of — its environment. If a body is required, the form of embodiment must still be specified [35]. This is significant because, in the emergent paradigm at least, the ability of two cognitive agents to communicate effectively requires them to have similar embodiments so that they have a shared history of interaction and a common epistemology.

The extent to which a cognitive system requires a capacity for development and, if so, the mechanisms by which development can take place are both open problems. In natural systems, growth is normally associated with development. However, growth in artificial systems remains a distant goal, although one whose achievement would open up many avenues of fruitful enquiry in cognitive systems. For current state-of-the-art cognitive systems, one can define development as the process by which a system discovers for itself the models that characterize its interactions with its environment. This contrasts with learning as the process whereby the parameters of an existing model are estimated or improved. Development, then, requires a capacity for self-modification [36] and in embodied emergent systems leads to an increased repertoire of effective actions and a greater ability to anticipate the need for and outcome of future actions [27].

The capacity to develop introduces another open issue: the minimal phylogenetic configuration — i.e., the perceptual, cognitive, and motoric capabilities with which a system is endowed at 'birth' — that is required to facilitate subsequent ontogenesis — i.e., development and learning through exploration and social interaction [27]. This issue is related to the specification of the system's cognitive architecture and the necessary and sufficient conditions that must be satisfied for cognitive behaviour to occur in a system. In addressing these issues, there is a trade-off between the initial phylogeny and the potential for subsequent development. This tradeoff is reflected by the existince of two types of species in nature: precocial and altricial. Precocial species are those that are born with well-developed behaviours, skills, and abilities which are the direct result of their genetic make-up (*i.e.* their phylogenic configuration). As a result, precocial species tend to be quite independent at birth. Altricial species, on the other hand, are born with poor or undeveloped behaviours and skills, and are highly-dependent for support. However, in contrast to precocial species, they proceed to learn complex cognitive skills over their life-time (*i.e.* through ontogenetic development). The precocial and the altricial effectively define a spectrum of possible configurations of phylogenetic configuration and ontogenetic potential [37]. The problem is to identify a feasible point in this spectrum that will yield a cognitive system capable of developing the skills we require of it.

Autonomy is a crucial issue for cognitive systems [38] but the degree of autonomy required is unclear. To an extent, it depends on how autonomy is defined and which paradigm of cognition is being considered. Definitions range from self-regulation and homeostasis to the ability of a system to contribute to its own persistence [39]. In the former case, self-regulation is often cast as a form of self-control so that the systems can operate without interference from some outside agent, such as a human user. In the latter case, autonomy is the self-maintaining organizational feature of living creatures that enables them to use their own capacities to manage their interactions with the world in order to remain viable [14]. Cognitivist systems tend to adopt the former definition, emergent systems, the latter.

Broadly speaking, cognitivist systems exploit symbolic representations while emergent systems exploit sub-symbolic state-based representations, with hybrid systems using both. The manner in which cognitivist and hybrids systems ground their symbolic representations in experience is still an open issue [40], with some arguing for a bottom-up approach [41] and others for a process of learned association, where meaning is attached rather than grounded [37].

The opening definition of a cognitive system states that it can act to achieve goals. The specification of these goals poses a significant challenge due to the autonomous nature of cognitive systems. It is more easily resolved for cognitivist systems since the goals can be hard-wired into the cognitive architecture. It is less clear how goals can be specified in an emergent system since the over-arching goal here is the maintenance of the system's autonomy. The goals of such a system reflect its intrinsic motivations and its associated value system [42]. The problem is to understand how to engineer this value system to ensure that the system is motivated to act in a way that satisfies goals which are external to the system and to decide how these goals can be communicated to the system.

Ideally, in addition to the characteristics of a cognitive system listed in the opening definition — autonomy, perception, learning, anticipation, goal-directed action, and adaptation — a cognitive computer system should also be able to say what it is doing and why it is doing it, i.e., it should be able to explain the reasons for an action [43]. This would enable the system to identify potential problems which might appear when carrying out a task and it would know when it needed new information in order to complete that task. Consequently, a cognitive system would be able to view a problem in several different ways and to look at different alternative ways of tackling it. In a sense, this is something similar to the issue discussed above about cognition involving an ability to anticipate the need for actions and their outcome. The difference in this case is that the cognitive system is considering not just one but many possible sets of needs and outcomes. In a sense, it is adapting *before* things don't go according to plan. From this point of view, cognition also involves a sense of self-reflection.

Cognitive systems also learn from experience and adapt to changing circumstances. To do this, the system must have some capacity for generalization so that concepts can be formed from specific instances and so that knowledge and know-how can be transferred from one context to another. This capacity would allow the system to adapt to new application scenarios and to explore the hypothetical situations that arise from the self-reflection mentioned above. It is unclear at present how such generalized conceptual knowledge and know-how should be generated, represented, and incorporated into the system dynamics.

Perception and action have been demonstrated to be co-dependent in biological systems. Perceptual development depends on what actions an infant is capable of and what use objects and events afford in the light of these capabilities. This idea of the action-dependent perceptual interpretation of an object is referred to as its affordance [44]. In neuroscience, the tight relationship between action and perception is exemplified by the presence of mirror neurons, neurons that become active when an action is performed and when the action or a similar action is observed being performed by another agent. It is significant that these neurons are specific to the goal of the action and not the mechanics of carrying it out. The related Ideomotor Theory [45] asserts the existence of such a common or co-joint representational framework for perception and action. Such a framework would facilitate the inference of intention and the anticipation of an outcome of an event due to the goal-oriented nature of the action. The realization of and effective co-joint perception-action framework remains an important challenge for cognitivist and emergent approaches alike.

Although clearly there are some fundamental differences between the cognitivist and the emergent paradigms, the gap between the two shows some signs of narrowing. This is mainly due to (i) a recent movement on the part of proponents of the cognitivist paradigm to assert the fundamentally-important role played by action and perception in the realization of a cognitive system [32]; (ii) the move away from the view that internal symbolic representations are the only valid form of representation [2]; and (iii) the weakening of the dependence on embedded a priori knowledge and the attendant increased reliance on machine learning and statistical frameworks both for tuning system parameters and the acquisition of new knowledge. This suggests that hybrid approaches may be the way forward, especially if a principled synthesis of cognitivist and emergent approaches is possible, such as 'dynamic computationalism' [2] or 'computational mechanics' [46]. Hybrid approaches appear to many to offer the best of both worlds — the adaptability of emergent systems and the advanced starting point of cognitivist systems — since the representational invariances and representational frameworks don't have to be learned but can be designed in and since the system populates these representational frameworks through learning and experience. However, it is uncertain that one can successfully combine what are ultimately highly incompatible underlying philosophies. Opinion is divided, with arguments both for (e.g. [2,46,40]) and against (e.g. [47]).

Recommended Readings

[1] Varela, F.J. (1992). Whence perceptual meaning? A cartography of current ideas. In Varela, F.J., Dupuy, J.P., eds.: Understanding Origins – Contemporary Views on the Origin of Life, Mind and Society. Boston Studies in the Philosophy of Science, Dordrecht, Kluwer Academic Publishers 235–263

[2] Clark, A. (2001). Mindware – An Introduction to the Philosophy of Cognitive Science. Oxford University Press, New York

[3] Freeman, W.J., Núñez, R. (1999). Restoring to cognition the forgotten primacy of action, intention and emotion. Journal of Consciousness Studies **6**(11-12) ix–xix

[4] Winograd, T., Flores, F. (1986). Understanding Computers and Cognition – A New Foundation for Design. Addison-Wesley Publishing Company, Inc., Reading, Massachusetts

[5] Ross Ashby, W. (1957). An Introduction to Cybernetics. Chapman and Hall, London

[6] McCulloch, W.S., Pitts, W. (1943). A logical calculus of ideas immanent in nervous activity. Bulletin of Mathematical Biophysics **5** 115–133
[7] Ross Ashby, W. (1954). Design for a Brain. Chapman and Hall, London
[8] Newell, A., Simon, H.A. (1976). Computer science as empirical inquiry: Symbols and search. Communications of the Association for Computing Machinery **19** 113–126 Tenth Turing award lecture, ACM, 1975.
[9] Haugland, J., ed. (1997). Mind Design II: Philosophy, Psychology, Artificial Intelligence. MIT Press, Cambridge, Massachusetts
[10] Kelso, J.A.S. (1995). Dynamic Patterns – The Self-Organization of Brain and Behaviour. 3rd edn. MIT Press, Cambridge, MA
[11] Maturana, H., Varela, F. (1987). The Tree of Knowledge – The Biological Roots of Human Understanding. New Science Library, Boston & London
[12] von Glaserfeld, E. (1995). Radical Constructivism. RouteledgeFalmer, London
[13] Stewart, J., Gapenne, O., Di Paolo, E.A. (2011). Enaction: Toward a New Paradigm for Cognitive Science. MIT Press
[14] Christensen, W.D., Hooker, C.A. (2000). An interactivist-constructivist approach to intelligence: self-directed anticipative learning. Philosophical Psychology **13**(1) 5–45
[15] Medler, D.A. (1998). A brief history of connectionism. Neural Computing Surveys **1** 61–101
[16] Smolensky, P. (1996). Computational, dynamical, and statistical perspectives on the processing and learning problems in neural network theory. In Smolensky, P., Mozer, M.C., Rumelhart, D.E., eds.: Mathematical perspectives on neural networks. Erlbaum, Mahwah, NJ 1–15
[17] Reiter, R. (2001). Knowledge in Action: Logical Foundations for Specifying and Implementing Dynamical Systems. MIT Press, Cambridge, Massachusetts
[18] Thelen, E., Smith, L.B. (1994). A Dynamic Systems Approach to the Development of Cognition and Action. MIT Press / Bradford Books Series in Cognitive Psychology. MIT Press, Cambridge, Massachusetts
[19] Port, R.F., van Gelder, T. (1995). Mind as Motion – Explorations in the Dynamics of Cognition. Bradford Books, MIT Press, Cambridge, Massachusetts
[20] McClelland, J.L., Vallabha, G. (2006). Connectionist models of development: Mechanistic dynamical models with emergent dynamical properties. In Spencer, J.P., Thomas, M.S.C., McClelland, J.L., eds.: Toward a New Grand Theory of Development? Connectionism and Dynamic Systems Theory Re-Considered, New York, Oxford University Press
[21] Maturana, H.R., Varela, F.J. (1980). Autopoiesis and Cognition — The Realization of the Living. Boston Studies on the Philosophy of Science. D. Reidel Publishing Company, Dordrecht, Holland
[22] Varela, F., Thompson, E., Rosch, E. (1991). The Embodied Mind. MIT Press, Cambridge, MA
[23] Vernon, D. (2010). Enaction as a conceptual framework for development in cognitive robotics. Paladyn Journal of Behavioral Robotics **1**(2) 89–98

[24] Newell, A. (1990). Unified Theories of Cognition. Harvard University Press, Cambridge MA
[25] Newell, A. (1982). The knowledge level. Artificial Intelligence **18**(1) 87–127
[26] Anderson, J. (1999). Cognitive architectures in rational analysis. In van Lehn, K., ed.: Architectures for Intelligence. Lawrence Erlbaum Associates, Hillsdale, NJ 1–24
[27] Vernon, D., von Hofsten, C., Fadiga, L. (2010). A Roadmap for Cognitive Development in Humanoid Robots. Volume 11 of Cognitive Systems Monographs (COSMOS). Springer, Berlin
[28] Vernon, D., Furlong, D. (2007). Philosophical foundations of enactive AI. In Lungarella, M., Iida, F., Bongard, J.C., Pfeifer, R., eds.: 50 Years of AI. Volume LNAI 4850. Springer-Verlag, Heidelberg 53–62
[29] Froese, T., Ziemke, T. (2009). Enactive artificial intelligence: Investigating the systemic organization of life and mind. Artificial Intelligence **173** 466–500
[30] Langley, P., Laird, J.E., Rogers, S. (2009). Cognitive architectures: Research issues and challenges. Cognitive Systems Research **10**(2) 141–160
[31] Anderson, J.R., Bothell, D., Byrne, M.D., Douglass, S., Lebiere, C., Qin, Y. (2004). An integrated theory of the mind. Psychological Review **111**(4) 1036–1060
[32] Anderson, M.L. (2003). Embodied cognition: A field guide. Artificial Intelligence **149**(1) 91–130
[33] Steels, L. (2007). Fifty years of AI: From symbols to embodiment — and back. In Lungarella, M., Iida, F., Bongard, J.C., Pfeifer, R., eds.: 50 Years of AI. Volume LNAI 4850. Springer-Verlag, Heidelberg 18–28
[34] Vernon, D. (2008). Cognitive vision: The case for embodied perception. Image and Vision Computing **26**(1) 127–141
[35] Ziemke, T. (2003). What's that thing called embodiment? In Alterman, R., Kirsh, D., eds.: Proceedings of the 25th Annual Conference of the Cognitive Science Society. Lund University Cognitive Studies, Mahwah, NJ, Lawrence Erlbaum 1134–1139
[36] Weng, J. (2004). Developmental robotics: Theory and experiments. International Journal of Humanoid Robotics **1**(2) 199–236
[37] Sloman, A., Chappell, J. (2005). The altricial-precocial spectrum for robots. IJCAI '05 – 19th International Joint Conference on Artificial Intelligence, Edinburgh
[38] Varela, F. (1979). Principles of Biological Autonomy. Elsevier North Holland, New York
[39] Bickhard, M.H. (2000). Autonomy, function, and representation. Artificial Intelligence, Special Issue on Communication and Cognition **17**(3-4) 111–131
[40] Barsalou, L.W. (2010). Grounded cognition: Past, present, and future. Topics in Cognitive Science **2** 716–724
[41] Harnad, S. (1990). The symbol grounding problem. Physica D **42** 335–346
[42] Edelman, G.M. (2006). Second Nature: Brain Science and Human Knowledge. Yale University Press, New Haven and London

[43] Brachman, R.J. (2002). Systems that know what they're doing. IEEE Intelligent Systems **17**(6) 67–71
[44] Gibson, J.J. (1979). The Ecological Approach to Visual Perception. Houghton Mifflin, Boston
[45] Stock, A., Stock, C. (2004). A short history of ideo-motor action. Psychological research **68**(2–3) 176–188
[46] Crutchfield, J.P. (1998). Dynamical embodiment of computation in cognitive processes. Behavioural and Brain Sciences **21**(5) 635–637
[47] Christensen, W.D., Hooker, C.A. (2004). Representation and the meaning of life. In Clapin, H., Staines, P., Slezak, P., eds.: Representation in Mind: New Approaches to Mental Representation. Elsevier, Oxford 41–70