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The new wave in robot learning

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The new wave in robotics research began to blossom in the mid-1980s with the convergence of a number of seemingly diverse research trends. All of these were inspired, to different degrees, by biological systems and include neuro-computing, behavior-based robotics, artificial life, evolutionary methods and behavioral modeling. The new wave is, in a sense, situated between the high-level planning robotics of pre-1980s deliberative artificial intelligence (AI) and low-level control theory. It grew out of a drive for simplicity, adaptivity, and an attitude that "nature knows best"; natural stupiddity rather than Artificial Intelligence. It should be noted, however, there are many different levels of "biological plausibility" in the robotics literature. They range from general abstract intuitive notions of animal intelligence or behavior [6] to more detailed modeling of particular creatures, e.g. [2,9,23] or parts of the brain, e.g. [8]. Sometimes one can get the impression that there is a catalog of insect behaviors that researchers look up to label their robot behavior after it has been observed (no I do not have the reference). There is also a second generation or second-order group emerging who share the methods and general control ideas, but are not concerned with the biology.

In AI and cognitive science, there was, and still is, considerable interest in the notion of physically grounding cognition. Cognition mind and intelligence have been studied in vacuo as a glass box in a black world (as opposed to behaviorism which is about a black box in a transparent world) – the physical symbol system hypothesis [40]. Put very succinctly, the view is that mind is like a computer program and that intelligence arises from the manipulation of mental symbols. However, Searle [37], in his famous Chinese room argument, pointed out that in the symbolic models there are no causal connections between the symbols and the world, i.e. between the representation and the represented. In response, cognitivists have suggested connecting the symbol system to the world via transducers [34]. Harnad [17] argues a case for "grounding" elementary symbols with a real world "hook" such that complex symbols/concepts, like "zebra", could be constructed from elementary grounded ones, e.g. "horse" and "stripes". This is really like an extension of referential or denotational semantics (see [39] for a connectionist critique of the internalist trap).

Such lofty notions have been rejected by the more radical approaches in new wave robotics concerned with building intelligence from the bottom up. One stance is that representations, except in a limited sense, are not necessary for intelligence [7]; that the world is a good enough model of itself. Others, such as Varela et al. [46], stress the interaction of the robot and the world – ideas that owe much to Gibson [14] and Piaget's work on sensorimotor activity in infancy [31]. Many of these ideas are now being collected under the general banner of embodied cognition or *enaction* (see [51] for a discussion). There is also a drive towards bringing novel forms of connectionist representation into robotics [38]. All of these approaches have a commonality that makes them fit well within the themes of the new wave.

Like all new waves, the one in robotics has historical roots too numerous to mention. We could go back to

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the French philosopher Rene Descartes (1596–1650) with his mechanistic and deterministic (clockwork) view of animal life. Among the more modern precursors is the important work of Loeb [26] who, in the early 1900s, took ideas, such as phototropism, from botany and applied them to animal behavior (the roots of reactive behavior). More important, for new wave robotics, is the pioneering work of the British scientist Walter [47] who, between 1948 and 1949, built the turtles Elmer and Elsie. One of these archetypes of the new wave was photographed at very lengthy exposure times while it moved about its business with a candle on its top. The resulting photographs showed traces of goal finding (a light source) and avoidance behaviors. [1]

Finally, we must not forget the theoretical and inspirational significance of neuro-anatomist Braitenberg's little 1984 book *Vehicles: Experiments in Synthetic Psychology* [5]. Braitenberg, clearly influenced by Loeb (see [4]), described how what appeared to be sophisticated and complex behaviors could be reproduced using a vehicle with only direct "neural" connections between simple sensors and motors. Thus the model of the world was the world itself. The inspirational part of the work was in the explanation of how behaviors which we might normally associate with mental activity appear to be created with such limited resources and direct wiring; these included fear and aggression (i.e. running from shadows, or hiding in dark places and pouncing on prey) and even went as far as love. See also Lloyd's [25] philosophical thesis extending Braitenberg's ideas to the notion of a simple mind.

Probably the biggest change between the precursors of the new wave and the new wave itself is the modeling of adaptive processes using computational learning mechanisms (though not always, see, e.g. [27]). Much of this has been as a response to successful research activity in computational learning over the last 10 years. The impact of standard machine learning techniques for robotics has already been noted [45]. The remarkable level of activity in neural network or connectionist learning over this period has been seen in many disparate fields from financial forecasting to analysis of chemicals, to manufacturing to modeling the mind and the nervous system. Indeed the majority of papers in this issue reflect the growing use of neural network architectures and learning methods for robot control.

There are a number of different ways in which the papers could have been ordered and classified here. For example, they could be classified according to type, size, or method of locomotion of the robots. The robot platforms ranged from the little wheeled Khepera through 2-, 4- and 6-legged "walkers" to CMU's Navlab road vehicle. The papers could also have been clustered according to the tasks used in the experiments but these were very varied. They include the popular obstacle, garbage recycling, maze learning, following the trainer, playing fetch, controlling walking and turning, driving a road vehicle, operating a disembodied arm, deciding on landmarks, localizing, and wandering. However, since the focus of the special issue is on learning, the articles were collated according to the class of learning methods used. There were four general classes: evolutionary methods, reinforcement learning (included all three papers describing legged locomotion papers), supervised learning, and individual methods which include learning by experiment, imitation, and learning from place.

Evolution methods. Evolutionary methods represent a very popular style of learning in the new wave of robotics, particularly for those interested in (though not exclusively) artificial life. These methods have been used for difficult computing problems for some time, e.g. [16,21], in a way that is abstractly analogous to real evolutionary theory, i.e. there is a fitness function to decide how fit a particular program is in the context of the problem it is to solve and there are mutation and crossover to operate on the computer equivalent of gene strings. Given the intended relationship between the behavior of new wave robots and natural biological behavior, the development of an *evolutionary robotics* is a very important step. Even from a purely engineering perspective, evolutionary methods are a very useful tool when working in unknown domains (but see [28] for a review and discussion of some of the problems).

The three "evolutionary" papers presented in this special issue show some of the variety of recent approaches. All of the papers use a mixture of simulation

[1] One of the original turtles was rediscovered in 1995 and has been restored and housed in the burden Neurological Institute in Bristol, UK.

and real robots (for testing and tuning). This is because, with current battery technology and hardware training times would be much too lengthy on physical robots. The methods used are different. Two of the papers employ evolutionary methods (genetic algorithms and evolution strategies) for developing neural net controllers while the third uses a genetic algorithm (GA) for building behavioral hierarchies from behavior primitives. The tasks range from maze learning to object avoidnace to garbage collection.

In the first paper, Nolfi provides an impressive demonstration of how a GA can be used to develop robot controllers for a non-trivial garbage collection task. The focus of the paper is on the use of a mutation operator and a fitness function that allows approximation to the desired behavior. The GA is shown to develop an effective single layer neural network to control a Khepera robot. The task was for the robot to learn to keep an arena clean by picking up cylinders and moving them an arena wall. In the evolutionary process, the fitness of a robot was calculated on the basis of how well it approximated a component of the task (e.g. moving close to a cylinder).

Salomon compares the performance of GAs with that of evolution strategies for developing neural net controllers for speedy obstacle avoidance on a Braitenberg vehicle. In two sets of experiments two different types of neural network architecture were employed. In the first experiment, a single matrix of weights connecting sensors directly to motors was evolved. In the second, a receptive field (radial basis function) network was evolved. The upshot being that in all cases, the desired behavior was obtained, but it was faster in the case of the evolution strategy method. It is interesting to compare this work with that of Touzet (this issue) in which essentially the same task is learned by a Khepera robot using reinforcement learning.

Wilson et al. add to the behavior-based literature by showing how a GA can be used on defined primitive behaviors to build behavioral hierarchies that can be used for more complex behaviors. They employ an iterative 4-phase GA method in which useful strings (8 elements long) of a primitive behavioral alphabet are first created. These are later *chunked* into larger strings for controlling a Lego robot in a maze. Both crossover and mutation operators are used but the main focus is on crossover for breeding. The method is shown to successfully evolve behavioral hierarchies.

Reinforcement learning. Another popular learning technique in current robotics is the general class of reinforcement or reward learning (RL). RL has been studied in psychology since the end of the 19th century with the work of the Russian behavioral psychologist Pavlov [30] on classical conditioning and the work of the connectionist, Thorndike [44], on *cage escape.* Pavlov showed how a stimulus arbitrarily paired with some unconditioned behavior, such as salivating to the sight and smell of food, can evoke the same behavior in the absence of the unconditioned stimulus (the food). The American behaviorists, led by Watson [49], pushed the idea that an animal's response is a reaction or adjustment to stimuli or complexes of stimuli. Skinner [41] developed a convincing argument, based on a large number of objective experiments, that animal behavior can be analyzed functionally in terms of combinations of stimulus and response. It is really Skinner's work on operant or instrumental condditioning that forms the historical foundation for modern RL techniques. He showed, for example, how to condition behavior by rewarding successive approximations to the desired behavior (shaping). But a central focus of Skinner's work was on detailing the effectiveness of different reinforcement contingencies on shaping and maintaining behavior – a point not taken up in robot learning as yet.

Like evolutionary methods, an advantage of RL is that it can be used in unknown environments or tasks. There are many RL techniques available to the robotics researcher, e.g. [1,42,48], that may or may not be implemented using neural nets, although that is the main method used in all but one of the five RL papers in this issue. It is also worth looking at Krose's *Robotics and Autonomous Systems*, special issue on Reinforcement Learning [22]. The first two papers in the current RL section deal with training wheeled robots on tasks such as avoiding obstacles as well as fetch and follow the trainer. The other three papers focus on training legged robots. In order, these papers are concerned with biped, quadruped, and sexaped walking. All five papers explore different methods of RL.

Saksida et al. use a model of animal reinforcement learning to drive a mobile robot. Their *shaping* model differs from several other methods of robot shaping in that it uses the RL technique to modify innate behaviors (rather like real animal training) and utilizes a human trainer than a programmed reinforcer. Initially, the robot has three categories of objects: a bright orange jacket, green and pink plastic dog toys and blue plastic recycling bins. One of its innate behaviors was to approach the plastic dog toys and pick them up. The experiments reported here show successful (fast) shaping of a number of new behaviors including, *follow the trainer* and *recycling and playing fetch.* The paper ends with a useful review of the differences between this research and other researches employing the term *shaping* for robot learning.

Touzet conducts a comprehensive comparative study on different implementations of Q-learning for use with a Khepera robot learning obstacle avoidance. The aim is to develop a Q-learning method with better generalization. The implementations compared here include weighted Hamming distance, statistical clustering, Dyna-Q, QCON, competitive multi-layer perceptrons, and self-organizing maps with Q-KOHON. In many ways this paper represents a new drive towards quantification in autonomous robotics research. Two main measures are used to analyze the results of the experiments: distance to objects over time and the proportion of moves executed by the obstacle avoidance module that receive positive reinforcement. The results suggest that generalization performance is best when Q-learning is implemented with neural learning techniques such as the competitive multilayer perceptron and Q-KOHON.

Legged locomotion. Benbrahim and Franklin present the use of a new RL algorithm for training a two-legged robot to walk. The RL algorithm, based on the cerebellar model arithmetic computer (CMAC), was employed to train a biped robot without exploiting any a priori knowledge of the domain. The main problem they tackled was the use of RL in a continuous action domain. This was solved using different modules consisting of simple controllers and small-scale neural nets. The results of the study show success in dealing with large numbers of inputs, knowledge integration and task definition.

Huber and Grupen advocate the effective interaction between native (innate) structure and adaptive processes in order to facilitate the acquisition of behavior in which there is an enormous range of policies from which to choose. The paper describes mechanisms for constraining and shaping the construction of behavior using techniques from discrete event dynamic system (DEDS) and shows how RL techniques may be employed to synthesize behavior on-line. The applicability of the approach is demonstrated by using the architecture and method to accomplish a rotation task in the quadruped walking domain.

Ilg et al. show how different learning methods may be integrated for the task of controlling a six-legged insect-like robot. There are two distinct phases to the proposed learning method. In the first phase, supervised learning on a radial basis function net sets up a prototypical control strategy. In the second phase, based on the primeval functionality developed in phase one, the control strategy is optimized and adapted to new tasks using the adaptive heuristic critic for RL. The effectiveness of the method is demonstrated in a favorable comparison with a pure RL approach.

Supervised learning. Supervised learning represented the beginnings of ANN learning in the 1950s and 1960s (although so-called Hebbian learning had been suggested in the 1890s by James [19] and informally presented by Hebb in his 1949 book [18]) with the perceptron convergence rule and the Widrow–Hoff rule [50]. It was later noted that a very powerful theory of animal learning, the Rescorla–Wagner rule [35], was essentially equivalent to the Widrow–Hoff rule (see [15,43]). It was the generalized version of the supervised learning for multi-layer perceptrons that formed the main thrust of the modern incarnation of connectionism or neuro-computing. The discovery (or re-discovery) of backpropagation learning for multilayer perceptrons by Rumelhart et al. in 1986 [36] led the way for a raft of new learning methods; mainly architectural variations of the feedforward networks for which backpropagation was designed, e.g. [12,20,32].

The problem with supervised learning for robotics is that a precise teaching signal is required to form the error terms at every time step. It is a data fitting or function approximation method in which the error signal is derived from a comparison of the output vector to an ideal vector (teaching signal). Evolutionary methods and RL tell a net only whether its behavior is "good" or "bad" or give it a "goodness" or "badness" value, e.g. fitness, which often makes learning slower and less precise. Their advantage is that exact domain knowledge is required outside of designing reinforcement contingencies and fitness. When backpropagation is used for RL, information from the reinforcement signal must be used to create the teaching signal [29].

The two papers in this section employ teaching signals that are derived directly from operating within the domains. Both papers use backpropagation for the construction of ANN systems consisting of more than one net. They both exploit the information contained in the hidden unit vectors (internal representations) of multi-layer perceptrons.

Baluja and Pomerleau present an artificial neural network learning approach to handle scenes which were difficult for Pomerleau's [33] earlier autonomous lane following system (ALVINN). ALVINN is the road following module of the CMU Navlab-5 Vehicle. The system presented here used an architecture constructed with backpropagation in two different stages. In the first stage a feedforward network was trained to output steering instruction for the Navlab vehicle. Then the structure of the hidden unit vectors was exploited by training a second net to take the current hidden units as input and to output the expected next input vector (image). These task-specific expectations were then used to attenuate input which did not match their expected values. The system was shown to be robust to many forms of distracting input features such as extra lane markings and passing cars

Sharkey discusses way it could be useful to explicitly bring connectionist representation theory into new wave robotics. This offers an alternative position to both the strong representational stance of AI and the anti-representational stance of reactive robotics (see paragraphs 2 and 3 of this editorial). Building on the cognitive science literature on connectionist representation he puts experiential representations to work in a decentered control task, the *disembodied arm problem*, in which a mobile robot operates an arm fixed to a table to pick up objects. There is no physical linkage between the arm and the robot and so the robot's point of view must be decentered. This is done by developing a modular artificial neural net system in three stages: (i) a classifier net is trained with laser scan data to develop transformationally invariant representations; (ii) an arm net is trained for picking up objects; (iii) an inter net is trained to communicate and coordinate the sensing and acting. The completed system is shown to create new non-symbolic transformationally invariant representations in order to perform the effective generalization of decentered viewpoints. The results are discussed in terms of building a distributed creature and an incremental intelligence.

Individual methods. The final group of papers are clustered because each uses an individual non-standard learning method. In the first paper principle components analysis is employed in a novel way as part of a robot system. The final two papers are complementary in that they are both dealing with robot localization problems, but at different stages – figuring out a good landmark to use in an unknown environment versus using prior knowledge to localize in a known environment – and they use different learning methods.

Voyles et al. present a method of *learning by observation*. Primitive gesture classes (sensorimotor primitives) are extracted from the raw sensor information and passed onto multi-agent networks to extract the demonstrator's "intended" moves with respect to the system's skill base. The learning technique is based on the successful application of principle components analysis to the extraction and identification of robotic sensorimotor primitives from teleoperated actions on both a mobile and a manipulator. This paper has some close relationships to the whole notion of imitation learning which has to be a step forward towards a higher-level intelligent robotics.

Murphy et al. investigate a method of robot localization by learning a triple of landmarks for each neighborhood in unknown environments. The problem is that the robot does not know a priori which landmarks are best to choose to (a) ensure that it can return to the locale from any chosen direction and recognize where it is; and (b) minimize the cost of recognizing landmarks, e.g. energy efficiency and effort. This is particularly important for hazardous or remote environments where there is little opportunity for maintenance or other human intervention. The presented solution, in brief, is to have the robot learn the "best" landmarks by a process of experimentation using active perception.

Harris and Reece use a high-level model of the hippocampus functioning is the rat to tackle the problem of *absolute localization* for a robot system. They augmented an existing robot control system developed in their laboratory [24] that was used to construct full metric maps of the target environment. The new learning mechanism involves storing an egocentric map for each place that the robot has visited. Each map is stored as a place unit, by analogy with *place cells* in the rat hippocampus, and an evidence collection search is conducted to determine which place units (egocentric maps) fire. This allows the robot to be set in the room with no initial location information and, with the help of its place cells, localize its position and move directly to its goal without further exploration.

Conclusions. The new wave in robotics is formed by a coalition of many different types of research and motivations. On the one hand, the motivation may be to test neural, biological or psychological models or it may be to test a general theory of adaptive behavior. On the other hand, the motivation may be to develop simple and efficient bottom-up robot controllers and to use the work from natural systems as an unconstraining inspiration. As the whole field progresses it offers many tools for the engineer and for the AI researcher. There are many ambitious ideas around about developing new life forms from the bottomup with evolution and there are ambitions towards developing an embodied cognition as a new form of AI. At present the outlook for moving to the next level of intelligence looks fraught with difficulties and a rocky road is indicated. Nonetheless, such high ambitions can be very healthy in a developing field.

The future looks very promising for the new wave in robotics. Workshop and special issue announcements are coming out at an almost weekly rate over the Internet and there are many off-shoots at engineering, AI, neural computing, and genetic algorithms conferences. The number of international contests for robots such as robot soccer, robot wars and micromouse is rapidly increasing and, at present, the media in the UK are taking a keen interest. This interest is encouraging research at both the amateur and professional levels and at some of the workshops there is an atmosphere of being at the "wild" frontier. These are all good indicators of the rise of interest in modern robotics research.

The papers in this special issue show some of the breadth of research in the new wave of robotics. While they do not cover every aspect, they provide a rich source of references across a large spectrum of the research. Other useful sources are [3,10,11,13,22]. It is clear from these sources that modern robotics has become a tough test-bed and an interdisciplinary melting pot computational learning theories. With sensor uncertainty, limited hardware and unpredictable environments, the flexibility, simplicity, and adaptability of controllers become paramount for the new wave.

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References

[1] A.G. Barto, R.S. Sutton, C.W. Anderson, Neurolike adaptive elements that can solve difficult learning and control problems, IEEE Transactions on Systems, Man, and Cybernetics, SMC-13 (1983) 834–846.

[2] R.D. Beer, H.J. Chiel, The neural basis of behavioral choice in an artifical insect, in: J.-A. Meyer, S.W. Wilson (Eds.), From Animals to Animats, First International Conference on Simulation of Adaptive Behavior, 1991, pp. 247–254.

[3] G.A. Bekey, K.Y. Goldberg (Eds.), Neural Networks in Robotics, Kluwer Academic Publishers, Boston, MA, 1993.

[4] V. Braitenberg, Taxis, kinesis and decussation, Progress in Brain Research 17 (1965) 210–222.

[5] V. Braitenberg, Vehicles, Experiments in Synthetic Psychology, MIT Press, Cambridge, MA, 1984.

[6] R.A. Brooks, A robust layered control system for a mobile robot, IEEE J. Rob. Autom. RA 2 (1986) 14–23.

[7] R.A. Brooks, Intelligence without representation, Artificial Intelligence 47 (1991) 139–159.

[8] N. Burgess, J.G. Donnett, J. O'Keefe, Robotic and neuronal simulation of hippocampal navigation, in: N. Sharkey, U. Nehmzow (Eds.), AISB-97 Workshop on Spatial Reasoning in Mobile Robots and Animals. Published as a Department of Computer Science Technical Report at Manchester University, UMCS-97-4-1, ISSN 1361–6161, 1997, pp. 113–121.

[9] D. Cliff, The computational hoverfly; a study in computational neuroethology, in: J.-A. Meyer, S.W. Wilson (Eds.), From Animals to Animats, First International Conference on Simulation of Adaptive Behavior, 1991, pp. 87–96.

[10] J.H. Connell, Mahadevan (Eds.), Robot Learning, Kluwer Academic Publishers, Reading, MA, 1993.

[11] M. Dorigo (Ed.), Special issue on learning autonomous robots, IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics 26 (3) (1996).

[12] J.L. Elman, Finding structure in time, Technical Report CRL Technical Report 8801, Center for Research in Language, University of California, San Diego, 1988.

[13] P. Gaussier (Ed.), Special issue on moving the frontiers between robotics and biology, Robotics and Autonomous Systems 16 (1996).

[14] J.J. Gibson, An Ecological Approach to Visual Perception, Houghton Mifflin, Boston, MA, 1979.

[15] M.A. Gluck, G.H. Bower, From conditioning to catagory learning, An adaptive network model, Journal of Experimental Psychology, General, 117 (1988) 227–247.

[16] D.E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley, Reading, MA, 1989.

[17] S. Harnad, The symbol grounding problem, Physica D 42 (1990) 335–346.

[18] D.O. Hebb, The Organization of Behavior, Wiley, New York, 1949.

[19] W. James, Psychology, A Briefer Course, Harper, New York, 1892, reprinted in 1961.

[20] M.I. Jordan, Serial order, A parallel distributed processing approach, Technical Report 8604, Institute for Cognitive Science, 1986.

[21] J.R. Koza, Genetic Programming; On Programming Computers by Means of Natural Selection, MIT Press, Cambridge, MA, 1992.

[22] B. Krose (Ed.), Special issue on reinforcement learning and robotics, Robotics and Autonomous Systems 15 (1995).

[23] D. Lambrinos, M. Marinus, H. Kobayashi, T. Labhart, R. Pfeifer, R. Wehner, An autonomous agent navigating with a polarized light compass, Adaptive Behavior, in press.

[24] D. Lee, The Map-Building and Exploration Strategies of a Simple Sonar-Equipped Mobile Robot, Cambridge University Press, Cambridge, UK, 1996.

[25] D.E. Lloyd, Simple Minds, MIT Press, Cambridge, MA, 1989.

[26] J. Loeb, Forced Movements, Tropisms and Animal Conduct, Lippincott, Philadelphia, 1918.

[27] P. Maes, Designing Autonomous Agents, Theory and Practice from Biology to Engineering and Back, MIT Press, Cambridge, MA, 1990.

[28] M. Mataric, D. Cliff, Challenges in evolving controllers for physical robots, Robotics and Autonomous Systems 19 (1996).

[29] L.A. Meeden, G. McGraw, D. Blank, Emergent control and planning in an autonomous vehicle, in: Proceedings of the Fifteenth Annual Conference of the Cognitive Science Society, Lawrence Erbaum, Hillsdale, NJ, 1993, pp. 735–740

[30] I.P. Pavlov, Conditioned Reflexes, Oxford University Press, London, 1927.

[31] J. Piaget, The Origins of Intelligence in Children, International Universities Press, New York, 1952.

[32] J.B. Pollack, Recursive distributed representations, Artificial Intelligence 46 (1990) 77–105.

[33] D.A. Pomerleau, Neural Network Perception for Mobile Robot Guidance, Kluwer Academic Publishers, Boston, MA, 1993.

[34] Z.W. Pylyshyn, Computation and Cognition, MIT Press, Cambridge, MA, 1984.

[35] R.A. Rescorla, A.R. Wagner, A theory of Pavlovian conditioning: Variations in the effectiveness or reinforcement and non-reinforcement, in: A.H. Black, W.F. Prokasy (Eds.), Classical Conditioning II: Current Research and Theory, Appleton-Century-Crofts, New York, 1972.

[36] D.E. Rumelhart, G.E. Hinton, R.J. Williams, Learning internal representations by error propagation, in: D.E. Rumelhart, J.L. McClelland (Eds.), Parallel Distributed Processing: Explorations in the Microstructure of Cognition, MIT Press, Cambridge, MA, 1986.

[37] J. Searle, Minds, brains and programs, Behavioral and Brain Sciences 3 (1980) 417–424.

[38] N.E. Sharkey, J. Heemskerk, The neural mind and the robot, in: A.J. Browne (Ed.), Perpectives in Neural Computing, IOP Press, in press.

[39] N.E. Sharkey, S.A. Jackson, Three horns of the representational trilemma, in: V. Honavar, L. Uhr (Eds.), Artificial Intelligence and Neural Networks: Steps towards Principled Integration, Academic Press, Cambridge, MA, 1994, pp. 155–189.

[40] H.A. Simon, The Sciences of the Artificial, MIT Press, Cambridge, MA, 1969.

[41] B.F. Skinner, Science and Human Behavior, Macmillan, New York, 1953.

[42] R.S. Sutton, Temporal Credit Assignment in Reinforcement Learning, Ph.D. Thesis, University of Massachusetts, 1984.

[43] R.S. Sutton, A.G. Barto, Towards a modern theory of adaptive networks: Expectation and prediction, Psychological Review 88 (1981) 135–170.

[44] E.L. Thorndike, Animal intelligence: An experimental study of the associative processes in animals, Psychological Review (Monograph Supplement) 2 (1898).

[45] W. Van de Velde (Ed.), Towards learning robots, Special issue of Robotics and Autonomous systems 8 (1–2) (1993).

[46] F.J. Varela, E. Thompson, E. Rosch, The Embodied Mind: Cognitive Science and Human Experience, MIT Press, Cambridge, MA, 1991.

[47] G. Walter, The Living Brain, Norton, New York, 1953.

[48] C.J.C.H. Watkins, Learning From Delayed Rewards, Ph.D. Thesis, King's College, 1989.

[49] J.B. Watson, Psychology From the Standpoint of a Behaviorist, Lippincott, Philadelphia, 1919.

[50] G. Widrow, M.E. Hoff, Adaptive switching circuits, Institute of Radio Engineers, Western Electronic Show and Convention, Convention Record 4 (1960) 96–194.

[51] T. Ziemke, Rethinking grounding, in: A. Riegler, M. Peschi (Eds.), Does Representation Need Reality? Proceeding of New Trends in Cognitive Science, Austrian Society for Cognitive Science, Vienna, Austria, 1997, pp. 87–94.

Will robots really steal our jobs? 1. Summary. Artificial intelligence (AI), robotics and other forms of â€˜smart automationâ€™ are advancing at a rapid pace and have the potential to bring great benefits to the economy, by boosting productivity and creating new and better products and services.Â Further discussion of how people can be helped to adapt to new technologies is contained in our Workforce of the Future report here: https://www.pwc.com/futureworkforce. An international analysis of the potential long term impact of automation. PwC â€¢ 4. Will robots really steal our jobs?Â Despite increasingly sophisticated machine learning algorithms being available and increasingly commoditised, it is these more fundamental computational job tasks that will be most impacted first. Towards multimodal neural robot learning Robotics and Autonomous Systems 47 (2004) 171â€“175. Abstract Learning by multimodal observation of vision and language offers a potentially powerful paradigm for robot learning. Recent experiments have shown that â€˜mirrorâ€™ neurons are activated when an action is being performed, perceived, or verbally referred to. Different input modalities are processed by distributed cortical neuron ensembles for leg, arm and head actions. In this overview paper we consider this evidence from mirror neurons by integrating motor, vision and language representations in a learning