

Analytical Review on the Correlation between Ai and Neuroscience

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Abstract: Neuroscience is the pragmatic study of brain anatomy and physiology. AI and neuroscience are typically related to the human brain's behavior. The alliance between artificial intelligence and neuroscience can produce an understanding of the mechanisms in the brain that generate human cognition. This paper discusses about the benefits that AI has got from the field of neuroscience. It basically deals with the learning, perception and reasoning. Neuroscience helps in understanding Natural Intelligence which correlates with the Artificial Intelligence. A bridge between AI and neuroscience is altercated.

Keywords: Neuroscience, Artificial Intelligence, Artificial Neural Network, Neuroethology, Hybrot.

I. Introduction

AI and neuroscience are the fields that come closest in engineering and biology. Artificial Intelligence has an important role to play in research, because artificial intelligence focuses on the mechanisms that generate intelligence and cognition (understanding). Artificial intelligence can also benefit from studying the neural mechanisms of cognition, because this research can acknowledge important information about the nature of intelligence and cognition itself. Natural adaptive and intelligent behavior is the result of complex interactions between nervous system, body and environment. Biological neural systems are embodied (represented) and embedded (enclosed). Because of this there has been a growing interest in using robots, employing on-board neural circuitry, to model aspects of animal behavior.

Neuroscientists study the nervous system. They apply a wide range of scientific inculcation: anatomy, biochemistry, computer science, pharmacology, physiology, psychology, and zoology. It's all about understanding how the brain and nervous system work, and it's one of the fastest growing areas of science.

Artificial neural networks became particularly popular in robotics because of a number of key properties, listed below, that had potential to overcome the weaknesses of traditional AI methods.

- They could generalize and deal with incomplete data.
- They could handle noisy data.
- They could adapt to emerging circumstances.
- By employing parallel distributed processing they offered a potentially more robust and efficient alternative to the sequential pipeline model of traditional AI.

The closely related area of computational neuroscience also came out of the shadows.

The prevailing hypothesis in both the neuroscience and AI literatures is that the brain recognizes its environment using optimized connections. These connections are determined through a gradual update of weights mediated by learning. The training and test distributions can be constrained to be similar so weights can be optimized for any arbitrary pattern. Thus both fields fit a mathematical-statistical framework that is well defined and elegant [1].

II. How Brain reinforces ai?

Brain has natural intelligence; if the same intelligence is developed in a machine then it leads to artificial intelligence. Brain is not similar to a digital computer because neuron's action potential is often referred to by the AI field as a biological implementation of a binary coding scheme. The brain cannot be contemplated to the CPU of digital computer because the brain's processor is neither central nor a unit. In digital computer the memory mechanisms are separable from processing mechanism which is not the case in brain. Brain is asynchronous and continuous [2] (works in discrete and sequential manner). The main attributes of brain are connectionism and parallelism. These attributes have been tried to implement in artificial neural networks. In Artificial Neural Network, the neurons in the input layer are connected with the neurons in the hidden layer and output layer. Artificial Neural Network works quite similar to the brain. NI has active perception towards the environment which is absent in AI. Our brain does not crave much training. Crick and Koch (1990), Llinas and Ribary (1993), Singer (1993), and Singer and Gray (1995) suggest that Consciousness

might be correlated with particular states of the brain involving coherent oscillations in the 40–70 Hz range, which would serve to bind together the percepts pertaining to a particular conscious moment [3]. The AI methods do not seem to scale to brain function. Synaptic plasticity is not been implemented yet. Synaptic plasticity is assumed to occur whenever a long lasting change in communication between two neurons occurs as a consequence of stimulating them simultaneously. The changes are labeled Long Term Potentiation (LTP) or Long Term Depression (LTD), if the responses increase or decrease respectively.

Fodor introduces the terms “horizontal” vs. “vertical” to describe two different sorts of decomposition or disintegration of intelligence. Horizontal decomposition identifies all the cognition processes and vertical decomposition identifies particular skills or faculties such as mathematics, language or metaphysics [4].

III. Paradigms of Neuroscience

The terminator is the best example of the bond between neuroscience and AI. The terminator is a life-life unit that has the capability of having psychological and cognitive functions. On the outside this robot looks human and because of the advancement of artificial intelligence, this robot is more human than ever. This robot has human traits on the surface and can interact with people as well as computers [5].

In 1949, Walter, a neurologist and cyberneticist based at the Burden Institute in Bristol, UK, who was also a world leader in EEG research, completed a pair of revolutionary machines he called ‘tortoises’. The devices were three-wheeled and sported a protective ‘shell’. They had a light sensor, touch sensor, propulsion motor, steering motor, and an electronic valve (vacuum tube) based analogue ‘nervous system’. [6] Walter said that even a simple nervous system could generate complex behavior.



Fig 1: Walter with his ‘tortoises’

The Lego MindStorms robotics kit consists of an infra-red tower, a programmable Lego brick (called the RCX - Robotic Control Explorer), a variety of sensors (light, actuator), several motors and normal Lego components (gears, pulleys, wheels, bricks etc)[7][8]. This kit can be used to build robots which are identified in the manuals provided, or to create your own custom-made robot. Extra sensors and parts can be purchased to add more functionality. Initially the programmable brick has no loaded operating system. The user can choose whether to upload the operating system supplied by Lego or upload an alternative operating system. The operating system is known as the Firmware. This operating system is called LeJOS (Lego Java Operating System). A fuzzy logic component was then coded in Java and included with the classes supplied to control the robot, as required by the end-user.

A mobile robot system nicknamed ‘Shakey’. The robot had a vision system which gave it the ability to perceive and model its environment in a limited way. Shakey could perform tasks that required planning, route-finding, and the rearrangement of simple objects [9]. It became a paradigm case for early AI driven robotics. The robot was provided with an initial set of axioms and then perceptual routines were used to build up and modify the world model based on sensory information, particularly from the robot’s vision system.

A more biologically inspired, and highly influential, example from the mid-1980s is Brook’s development of the hexapod robot Ghengis[10][11][12][13]. The body and control system for the robot, were directly inspired by insect neuroethology (evolutionary and comparative approach to the study of animal behavior and its underlying mechanistic control by the nervous systems [14][15][16]). A network of 57 augmented finite state machines

(AFSMs), including six repeated sub-networks (one for each leg), enabled the robot to walk over rough terrain and follow a person located by its infrared sensors. The networks can be thought of as a variety of hardwired dynamical neural network. They provided highly distributed efficient control and coordination of multiple parallel behaviors.

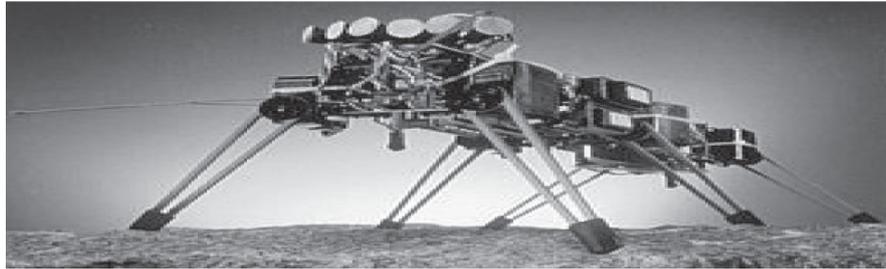


Fig 2: ALVINN

The system, known as ALVINN, using input from a camera, was able to learn in under 5 minutes to autonomously control the vehicle by watching the reactions of a human driver. ALVINN was successfully trained to drive in a variety of circumstances including single-lane paved and unpaved roads, and multilane lined and unlined roads, at speeds of up to 20 miles per hour. Although the system used a standard back-propagation scheme, results were impressive – in no small part due to the clever on-the-fly training scheme employed, which involved ‘additional’ scenarios generated by deliberately shifting the input images to simulate poor driving [17]. These systems were more robust than the previously designed systems.

Brain-based devices (BBDs) are neurobotic devices whose development is most closely associated with Edelman and colleagues at the Neurosciences Institute in San Diego. Edelman’s ‘Darwin’ series of BBDs has an extensive history dating back to 1990 [18] and continuing to the present day [19][20]. BBDs are constructed according to the methodology of synthetic neural modeling’, which has four key components [21]. First, a BBD needs to engage in a behavioral task. Second, its behavior must be controlled by a simulated nervous system having a design that reflects the brain’s architecture and dynamics. Third, it needs to be situated in the real world. And fourth, its behavior and the activity of its simulated nervous system must allow comparison with empirical data.

Subsumption architecture (Rodney Brooks): Subsumption architecture is a reactive robot architecture heavily associated with behavior-based robotics. The term was introduced by Rodney Brooks and colleagues in 1986 [22][23][24]. Subsumption has been widely influential in autonomous robotics and elsewhere in real-time AI. Subsumption architecture is a way of decomposing complicated intelligent behavior into many "simple" behavior modules, which are in turn organized into layers. Each layer implements a particular goal of the agent, and higher layers are increasingly abstract. Each layer's goal subsumes that of the underlying layers. For example, the decision to move forward by the eat-food layer takes into account the decision of the lowest obstacle avoidance layer. As opposed to more traditional AI approaches, subsumption architecture uses a bottom-up design. For example, a robot's lowest layer could be "avoid an object". On top of it would be the layer "wander around", which in turn lies under "explore the world". Each of these horizontal layers access all of the sensor data and generate actions for the actuators — the main caveat is that separate tasks can suppress (or overrule) inputs or inhibit outputs. This way, the lowest layers can work like fast-adapting mechanisms (e.g. reflexes), while the higher layers work to achieve the overall goal. Feedback is given mainly through the environment.

The main advantages of the methodology are:

- The modularity,
- The emphasis on iterative development & testing of real-time systems in their target domain, and
- The emphasis on connecting limited, task-specific perception directly to the expressed actions that require it.

The main disadvantages of this model are:

- The inability to have many layers, since the goals begin interfering with each other,
- The difficulty of designing action selection through highly distributed system of inhibition and suppression, and
- The consequent rather low flexibility at runtime.

Artificial Intelligence Robot (AIBO): This robot was invented by Sony Digital Creatures Lab and was launched in the year 1999. It is an iconic series of robotic pets designed and manufactured by Sony [25]. The

first customer model was introduced on May 11, 1999 [6]. There were three generations of this robot. First Generation came up with ERS-110 and ERS-111. Second generation came with ERS-210, ERS-300, ERS-300(Latte and Macaron), ERS-311 “Latte”, ERS-312 “Macaron”, ERS-220, ERS-210A/220A. Third generation models were ERS-7, ERS-7M2, and QRIO. These robots were used extensively in education. The AIBO has seen much use as an inexpensive platform for artificial intelligence education and research, because it integrates a computer, vision system and articulators in a package vastly cheaper than conventional research robots.

Sensory motor actions (James O. Regan): Sensorimotor approach allow to address the problem of the explanatory gap: that is, the problem of explaining perception, consciousness, and qualia in terms of physical and functional properties of perceptual systems. Vision, we argue, requires knowledge of sensorimotor contingencies. Vision requires the satisfaction of two basic conditions. First, the animal must be exploring the environment in a manner that is governed by the two main kinds of sensorimotor contingencies (those fixed by the visual apparatus, and those fixed by the character of objects). Second, the animal, or its brain, must be “tuned to” these laws of sensorimotor contingencies. That is, the animal must be actively exercising its mastery of these laws. Seeing is a way of acting. It is a particular way of exploring the environment. Activity in internal representations does not generate the experience of seeing. The outside world serves as its own, external, representation [26]. The experience of seeing occurs when the organism masters what we call the governing laws of sensorimotor contingency. The advantage of this approach is that it provides a natural and principled way of accounting for visual consciousness, and for the differences in the perceived quality of sensory experience in the different sensory modalities.

Hybrot: Hybrid neural-robotics for neuroscience research. A living neuronal network is cultured on a multi-electrode array (MEA) where its activity is recorded, processed in real time, and used to control a robotic or simulated embodiment, such as the K-Team Khepera or Koala (pictured at lower right). The robot’s input from proximity sensors is converted to electrical stimuli that are fed back to the neuronal network within milliseconds via a custom multi electrode stimulation system [27]. The hybrot’s brain (MEA culture) can be imaged continuously on the microscope while its body behaves and learns. The microscope is enclosed in an incubator (lower left) to maintain the health of the living network. This closed-loop Embodied Cultured Networks approach may shed light on the morphological correlates of memory formation, and provide AI researchers with ideas about how to build brain-style AI.

IV. Conclusion

The paper chronologically presents the connection between the neuroscience and artificial intelligence. It presents the various models that have proven to be the link between these two fields (neuroscience and artificial intelligence). Active perception has been the key concept in all the robots.

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References:

- [1] Tsvi Achler, Eyal Amir, Neuroscience and AI Share the Same Elegant Mathematical Trap.
- [2] Steve M. Potter, “What Can AI Get from Neuroscience?” M. Lungarella et al. (Eds.): 50 Years of AI, Festschrift, LNAI 4850, pp. 174–185, 2007. © Springer-Verlag Berlin Heidelberg 2007.
- [3] Llinas, R. & Ribary, U. (1993) Coherent 40-Hz oscillation characterizes dream state in humans. *Proceedings of the National Academy of Sciences USA* 90(5):2078–81.
- [4] Joanna J. Bryson, Modular Representations of Cognitive Phenomena in AI, Psychology and Neuroscience.
- [5] Jason Dhaliwala Cognitive Psychology, Cognitive Neuroscience and Artificial Intelligence.
- [6] P. Husbands, Philipides A., Computational Neuroscience for Advancing Artificial Intelligence: Models, Methods and Applications, Chapter 10, Published in the United States of America by Medical Information Science Reference (an imprint of IGI Global)
- [7] Stephen Kelly and Alfons Schuster, ‘APPLICATION OF A FUZZY CONTROLLER ON A LEGO MINDSTORMS ROBOT’
- [9] Nilsson, N. J. (Ed.). (1984). Shakey The Robot, Technical Note 323. AI Center, SRI International, Menlo Park CA., Nolfi, S., & Floreano, D. (2000) Evolutionary Robotics: The Biology, Intelligence, and Technology of Self-Organizing Machines. Cambridge, MA: MIT Press.
- [10] Brooks, R. A. (1986). A Robust Layered Control System for a Mobile Robot. *IEEE Journal on Robotics and Automation*, 2(1), 14–23. Brooks, R. A. (1989). A Robot that Walks; Emergent Behaviors from a Carefully Evolved Network. *Neural Computation*, 1(2), 253–262. doi:10.1162/neco.1989.1.2.253
- [12] Brooks, R. A. (1999). *Cambrian Intelligence: The Early History of the New AI*. Cambridge, MA: MIT Press.
- [13] Brooks, R. A. (2002). *Flesh and Machines: How Robots Will Change Us*. New York: Pantheon Books.
- [14] Hoyle, G. (1984) The Scope of Neuroethology. *The Behavioral and Brain Sciences*. 7:367–412.
- [15] Ewert, P. (1980) Neuroethology. Springer-Verlag. New York.
- [16] Camhi, J. (1984) Neuroethology. Sinauer. Sunderland Mass.

- [17] Pomerleau, D. (1991). Efficient Training of Artificial Neural Networks for Autonomous Navigation. *Neural Computation*, 3, 88–97. doi:10.1162/neco.1991.3.1.88.
- [18] Reeke, G. N., Sporns, O., & Edelman, G. M. (1990). Synthetic neural modeling: The “Darwin” series of recognition automata. *Proceedings of the IEEE*, 78(9), 1498–1530. doi:10.1109/5.58327
- [19] Fleischer, J. G. (2007). Retrospective and prospective responses arising in a modeled hippocampus during maze navigation by a brain-based device. *Proceedings of the National Academy of Sciences of the United States of America*, 104(9), 3556–3561. doi:10.1073/pnas.0611571104
- [21] McKinstry, J. L. (2008). Embodied models of delayed neural responses: spatiotemporal categorization and predictive motor control in brain based devices. *Neural Networks*, 21(4), 553–561. doi:10.1016/j.neunet.2008.01.004
- [22] Krichmar, J. L., Seth, A. K., Nitz, D. A., Fleischer, J. G., & Edelman, G. M. (2005b). Spatial navigation and causal analysis in a brain-based device modeling cortical-hippocampal interactions. *Neuroinformatics*, 3(3), 197–222. doi:10.1385/NI:3:3:197.
- [23] Brooks, R. (1986). "A robust layered control system for a mobile robot" (http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1087032). *Robotics and Automation, IEEE Journal of [legacy, pre-1988]* 2 (1): 14–23. doi:10.1109/JRA.1986.1087032. (<http://dx.doi.org/10.1109/JRA.1986.1087032>). Retrieved 2008-04-14.
- [24] Brooks, R. (1986). "Asynchronous distributed control system for a mobile robot." (<http://www.csa.com/partners/viewrecord.php?requester=gs&collection=TRD&recid=1481881CI>). *SPIE Conference on Mobile Robots*. pp. 77–84.
- [25] Brooks, R. A., "A Robust Programming Scheme for a Mobile Robot", *Proceedings of NATO Advanced Research Workshop on Languages for Sensor-Based Control in Robotics*, CastelvecchioPascoli, Italy, September 1986.
- [26] en.wikipedia.org/wiki/AIBO, archived at web citation.
- [27] J. Kevin O'Regan, A sensorimotor account of vision and visual consciousness, *BEHAVIORAL AND BRAIN SCIENCES* (2001) 24:5