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# Cognitive Robotics, Enactive Perception, and Learning in the Real World

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## Abstract

Robotic cognitive modeling in the real world requires a level of integration and grounding rarely seen in more abstract modeling. However, like Newell we believe this is exactly the kind of integration needed to promote scientific cumulation in the cognitive sciences. We present a neural model of learning compatible with Noë's account of enactive perception. We highlight that accounts of enactive perception tend to oversimplify the problem of identifying contingent relationships and introduce a novel way to address the problem of marginal regularities. Finally, we describe a general (non-task specific) model and present a number of real-world robotic experiments demonstrating a wide range of integrated psychological phenomena.

**Keywords:** Cognitive robotics; enactive perception; learning; cognitive modeling; association; reservoir systems; dynamic liquid association; liquid state machine; echo state network.

## Introduction: A Call for Integration

Although many of the pioneers of AI and cognitive science were very optimistic about the prospects of creating human-like general AI (Feigenbaum & Feldman, 1963; Simon, 1957), the field has not come even close to fulfilling such early promises. We believe that this is in part due to a lack of research directed specifically at the problem(s) of integration. Newell (1973) claimed that this limited progress was, in part, the result of using methods that do not support integrative and cumulative modeling: "Suppose that in the next thirty years we continued as we are now going. Another hundred phenomena give or take a few dozen, will have been discovered and explored. Another forty oppositions will have been posited and their resolution initiated. Will psychology then have come of age?" (ibid, pp. 287-288). Newell's opinion at the time, and borne out over the following thirty years, was that the answer must be no: "Far from providing the rungs of a ladder by which psychology gradually climbs to clarity, this form of conceptual structure leads rather to an ever increasing pile of issues, which we weary of or become diverted from, but never really settle." (ibid, p. 289). Clearly, Newell's comments and suggestions are still relevant to all forms of cognitive modeling from computational neuroscience to cognitive robotics, and are not limited solely to the symbolic methods he pursued himself.

Newell made three specific suggestions for the future development of psychological theories and models; "The first suggestion is to construct complete processing models rather than the partial ones we now do." (ibid, p. 301). He contrasted an implemented simulation with an abstract flow diagram,

claiming that the former was reasonably tight, in terms of theoretical explanation, while the latter left far too much unspecified and unconstrained. In updating our interpretations of Newell's first suggestion, even implemented simulations leave much unspecified and unconstrained by comparison to concrete robotic agents which must account for processing from the sensory surface all the way to motor output, only then can we claim to have a complete account of the phenomenon studied (cf. Brooks, 1989; Pfeifer & Scheier, 1999). That is not to claim that isolated or ungrounded models cannot provide significant contributions to cognitive theories, rather that such models typically remain silent on issues of integration and grounding. Hence, they are also at odds with the emerging paradigm of embodied cognition (e.g. Varela et al., 1991; Clark, 1997; Pfeifer & Scheier, 1999; Gibbs, 2005).

Newell's (1973) second and third suggestions were to "accept a single task and model all of it." (ibid, p. 303), or "to stay with the diverse collection of small experimental tasks, as now, but to construct a single system to perform them all... [and crucially] ...it must truly be a single system to provide the integration that we seek." (ibid, p. 305). Despite huge progress in modeling techniques, convincing answers to Newell's call for integration are very rare.

The natural way forward then for cognitive modeling, in our opinion, is – still pretty much in the spirit of Allen Newell's original view of cognitive modeling, although not necessarily following his choice of symbolic modeling approach – to aim for integrative and cumulative modeling. It is here that we believe modeling with situated and embodied agents is central, not only as real world modeling forces a shift in our focus from ungrounded theories of isolated phenomena to grounded and integrated models accounting for complete processing, but also for theoretical reasons in the embodied cognition paradigm (Morse & Ziemke, In Press).

## Perception, Action, and the Environment

Real world robotic embodiment plays a wider role than merely focusing our attention on matters of internal integration. The unit of analysis that many cognitive scientists consider relevant to our understanding of cognition has shifted from the view of cognition as purely internal computation that, at least to some degree, can be reduced to mapping sensory input to motor output, to the view of cognition as situated and embodied action that spans brain, body and environment (Clark, 1997; Clark & Chalmers, 1998; Hutchins, 1995; Suchman, 1987; Varela, Thompson, & Rosch, 1991). Thus embodiment calls our attention to the

relationship between an agent or organism and its environment. One prominent example of this is the enactive approach (Noë, 2004; O'Regan & Noë, 2001) in which perception is thought to be both dependent upon, and constituted by our possession of sensorimotor knowledge, i.e. “practical knowledge of the ways movement gives rise to changes in stimulation.” (Noë, 2004). Thus sensorimotor knowledge is not simply factual knowledge about a domain but is intimately about the relationship between an agent and its environment.

It is clear that the strong dynamic relationship between the developing agent and its environment is co-determining and thus to better understand cognition, modeling in real environments with robotic/embodied agents is important. Without refuting the importance of evolution, it seems reasonably clear that much of our human world knowledge and general cognitive ability is either derived from, or heavily shaped by, life-time experiences. The models discussed in this paper therefore address ontogenetic developmental models of human learning demonstrated on a real robot.

Models displaying cognitive abilities of one kind or another typically capture either knowledge or skill in a limited domain. In attempting to develop an integrative approach, and following Noë's enactive view, we can first collapse these two distinctions together; knowledge is skill, and skill is knowledge. Next, and still following Noë's enactive view, there is no special treatment of any particular modality or domain of data, so as long as contingencies in the agent's interactions with its environment are captured, perception of, and hence skill within any domain should be forthcoming. Our starting point for an integrated modeling approach then is to model a form of learning compatible with Noë's view of enactive perception. This then provides means for a real robotic agent to learn from its experience in noisy and unstructured environments in a domain general way, thereby integrating knowledge and skills from several domains of interaction.

### **Enactive Perception and Marginal Regularities**

According to the enactive view, there are regularities in the world which produce stereotypical changes in sensory stimuli relative to actions performed. To use an example from (Noë, 2004) a plate may appear to us as elliptical from some viewpoints but we know it to be in fact round and perceive it as such. This means that we know how it would look if we moved a little this way or a little that way, and we would be surprised if we did move and found those expectations contradicted. Our perception of a plate is to recognize that some part of our sensory input corresponds to a sensorimotor profile typical of plates – how we would expect our sensory input to change as a result of various actions. This is, Noë claims, how our perception gains content, though without an account of affect it is not clear how this content becomes meaningful. Despite this, it is clear that such knowledge could be extremely useful to an embodied cognitive agent; for example simulating or anticipating the effects of possible

actions for evaluation, and recognizing categories in an agent relative way.

Initially the enactive theory of perception would appear open to computational / robotic modeling; acquiring and representing sensorimotor profiles from experience would seem straight forward as they present contingent and hence contextually consistent relationships between our actions and our sensory data. One possible method to use would be statistical analysis from which consistent relationships in data are supposed to emerge; however, there are at least two problems complicating the application of such methods in modeling enactive perception. Firstly, there is a temporal problem as the result of an action may not be immediate, and may in fact result from a sequence of actions leading to a variation on the credit assignment problem (i.e. which subset of the actions performed is actually responsible for this sensory change). Secondly, and more problematically, there is the problem of marginal regularity. There are relatively few sensorimotor contingencies that emerge directly between our senses and actions, rather these contingencies lie between patterns of relationships in sensory data and patterns of relationships in action. For example the regularities or affordances offered by a cup are not consistently between the same retinal pixels and the same muscular actions. Initially this is worrying as by Noë's theory it is the identification of sensorimotor profiles that enables recognition of the objects in the first place. Acknowledging this problem turns Noë's account on its head; now it seems that you must have persistent recognition of the object over time (allowing for varying sensory contact) in order to perceive the contingencies it affords to your action. The initial object recognition or tracking need not be a conscious perception in itself but achieving this prior recognition presents a serious problem for computational / robotic modeling. As Kirsh (1992) put it, “what if so little of a regularity is present in the data that for all intents and purposes it would be totally serendipitous to strike upon it? It seems ... that such a demonstration would constitute a form of the poverty of stimulus argument” (ibid, p. 317). Such marginal regularities are present in the overwhelming majority of tasks requiring any kind of categorization, recognition, or decision making process based in either real world or any other non-trivial data set (Clark & Thornton, 1997). In recent years the reservoir systems approach has been developed with the potential to alleviate both problems, as discussed in more detail in the next section.

### **Reservoir Systems**

Two primary forms of reservoir system are the biologically derived Liquid State Machine (LSM) (Maass, Natschlag, & Markram, 2002a, 2002b, 2002c) and the more computationally efficient Echo State Network (ESN) (Jaeger, 2001a, 2001b, 2002). Although descriptions of reservoir systems can be quite complicated, what they all have in common is a sparse randomly interconnected network of artificial neurons in which activity coming into the system reverberates around the network, and would decay to a null

state if the input were stopped. Reservoir systems implement a high dimensional space and cast the input data into it. To explain the role of the reservoir, Maass et al draw an analogy between the activity reverberating around a reservoir and the ripples on a pond. Input to either system (e.g. dropping a stone into the water, or providing input to the reservoir) causes activity (or ripples) which then reverberate around the system, decaying over time. Just like the ripples on the pond, this residual activity is far from random and can be used to tell us something about the disturbance(s) that originally caused it, thus it carries information about those disturbance(s).

Reservoir systems also have interesting temporal dynamics as a disturbance at time  $t$  will persist within the reservoir lasting at least as long as the decay period (the time taken to reach a null state should input cease), and with feedback can potentially last even longer.

Normally a reservoir system, although untrained, would utilize trained perceptrons to act as readout units. These single layer perceptrons can only recover information from the reservoir so long as it is linearly separable; however, this need not be simple linear separation in the original input space but rather in the transformed and dynamic state space of the reservoir. In this standard guise reservoir systems would seem to tackle, at least in part, both of the problems identified with synthetically modeling Noë's (2004) account of enactive perception, though they still require the explicit training of readout perceptrons.

### **Dynamic Liquid Association**

Readers less interested in the implementation details of the model should pass over this section. The *Dynamic Liquid Association* (DLA) model (Morse, 2005a, 2005b, 2006) both removes the need for training readouts from the reservoir and implements an auto-associative network capturing multiple psychological phenomena. We know that the basic limitation of any simple statistical or experience-based learning system to accurately capture relationships is that the entities those relationships are between are linearly separable. Therefore if it is possible to train a single layer perceptron to act as a readout unit to a reservoir, responding differentially to the presence of a particular input feature, then, even without doing so we know (given the limitations of single layer perceptrons) that that feature must be linearly separable somewhere within the reservoir. By this logic the supervised training of readout units only localizes responses but does not provide any greater separation than is already present. Thus if we apply a context sensitive statistical or experience based learning algorithm directly to the microcircuit, it should behave as if all the features which could in principal be trained for identification by single layer perceptrons were explicitly represented anyway, i.e. the perceptron training becomes an unnecessary step. That means the limits imposed on statistical learning by requiring separation are extended to include all those features of the sensory data stream which are made linearly separable by the continual transformations of the reservoir. This is an important step differentiating this

method from others both technically and theoretically. Practically, this method does not require the kind of explicit training of readout units that both forces a localist interpretation and can be seen as fixing or providing the interpretations of those sensory states for which training is provided. The relationships statistically captured are driven by contextual consistencies in the sensorimotor experience of the agent and therefore conform to the generation of enacted sensorimotor profiles. That is to say, sensorimotor contingencies between an agent and its environment will be captured by the statistical analysis so long as the entities involved in the contingency are made separable by the reservoir. This is significantly more powerful than relying on the contingencies being between separable entities in the first place. Finally, the method remains uncommitted to any particular form of embodiment or sensory apparatus and should therefore be considered general purpose, requiring no task or embodiment-specific knowledge in advance.

Using this method in modeling enactive perception, the two major problems highlighted in the previous section are significantly alleviated. Firstly, the current state and trajectory of the reservoir are contingent not only on current events, but also recent events, thereby enabling contingencies between actions in the recent past and sensory changes, to be captured. Secondly, sensory input is continually transformed and warped in the high-dimensional space of the reservoir such that many of the marginal regularities are exposed. This is not to claim that these problems have been solved, rather to re-iterate, they are alleviated to some degree, but should still be considered as limitations to this model.

At this point the original direction of Noë's claims can be re-instated. Having begun forming sensorimotor profiles based on experienced contingencies between separable entities, such relationships can not only be used to predict the sensory effects of various actions, but could also strengthen the recognition / separation of these entities by feeding back into the reservoir (Jaeger, 2001b).

### **Auto-Association**

Following connectionist work on spreading activation models, a simple learning algorithm has been introduced for the ongoing construction of Interactive Activation and Competition (IAC) networks (Morse, 2003). Standard IAC models (McClelland, Rumelhart, & Group, 1986; Page, 2000; Young & Burton, 1999) consist of a number of localist (independently interpretable) units connected via designed connectivity to other localist units, such that activity spreads between related feature units while incompatible features compete. Unlike many architectures derived through evolution or gradient descent supervision, these networks function in a manner introspectively similar to mental activity, in that each locally represented thought, concept or idea primes related thoughts, concepts, and ideas as activity spreads between units via structured interconnections (Morse, 2005a, 2005b; Young & Burton, 1999). To autonomously develop similar architectures in conjunction with a reservoir

system, a unit sensitive to the current context is generated by autonomous pattern recognition over the current state of the reservoir. In the models presented here this is achieved using Adaptive Resonance Theory (ART) networks (Carpenter & Grossberg, 1987) as they allow for the ongoing identification of consistent patterns in subsections of an otherwise varying input vector.

The autonomously identified patterns are then fully connected to the reservoir and to motor action units by connections initially weighted at 0, and subject to normalized Hebbian and anti-Hebbian plasticity. It is these plastic connections that provide a simple statistical analysis and are intended to capture the contingencies present between actions and sense data in the contexts in which each particular pattern unit is active. As already discussed, the reservoir is intended to provide separation between complex features in the sensory data. Statistics directly between the reservoir and actions would not be context sensitive as the same units are involved in many different relationships. That is to say, the statistical relationships are mediated by the autonomous identification of sub-states of the reservoir such that different sub-states can result in different statistical relationships between the transformed sensory data and actions.

### Experiments - Cognitive Robotics

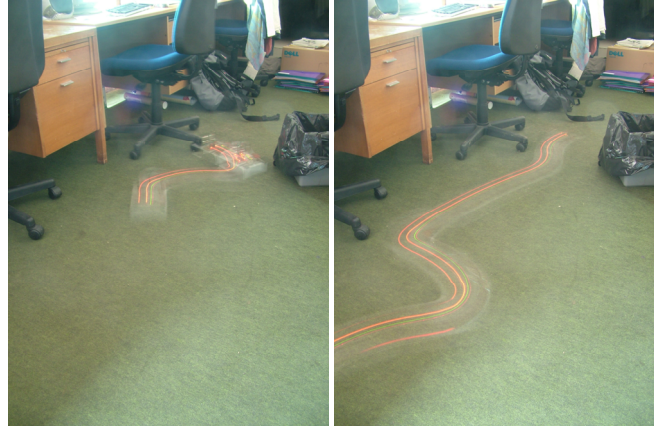
The DLA model described above is used as the control system for a real robot such that input from three forward facing infrared proximity sensors and six contact sensors (covering the front left and right, rear left and right, and left and right sides) provided input randomly but sparsely to the reservoir. In an additional set of experiments low-resolution input from a camera was also fed via random connectivity into the same reservoir. Four motor neurons were also set up in a winner-takes-all relationship corresponding to acceleration in the forward, backward, turn left, and turn right directions. Weak noise was used to initiate behaviour.

Finally a motivation neuron was included, active whenever any of the contact sensors became active. This neuron had plastic reciprocal connections inverting the polarity of incoming connections and amplifying their strengths. The effect of this neuron is to inhibit units in positive relations to it, while amplifying those in negative relationships. The practical upshot of this is to prevent actions leading to activity in the contact units, i.e. to prevent behavior expected to lead to a collision. For further details and full experimental analysis see Morse (2006).

### Summary of Results

**Obstacle Avoidance.** Placed in both simple and complex environments, the robot, initially having no task-specific knowledge wanders randomly around, occasionally colliding with obstacles. Following a short period ( $\approx 5$  min,  $\approx 1000$  time steps) with occasional collisions, the agent's behavior self-organizes to produce collision avoidance (see **Figure 1**). This result is not maintained when the reservoir is removed from the architecture and statistical learning applied directly to the input and output streams. Although the task here is simple,

the behaviour emerging from the agent is significantly more complex than that of a Braitenberg vehicle (Braitenberg, 1984). Agents frequently approach obstacles, only turning or backing away at the very last moment. Some experienced agents 1hour+ were even able to perform extremely close range movement without colliding.



**Figure 1:** 15 second time laps pictures showing (left) initial collisions from which the robot learned (right) to successfully navigate a real office environment without further collisions

**Classical Conditioning.** Following Pavlov's (1927) description of classical conditioning, a conditioned response will be elicited by any stimulus that is conditioned by repeated exposure to a pairing of that stimulus with one normally eliciting a reflex response. To demonstrate this with complex sensory input, the DLA agent's robotic embodiment is modified to include visual input from a pan-tilt camera, and an additional input (a button press), which is directly connected to the motor output so as to force the agent to move forward. This hard-wired behavior can be considered analogous to a reflex response such as the salivation response elicited in the presence of food by Pavlov's dogs. Thus, when the new input button is pressed, the robot necessarily (by hard-wired reflex) moves forward.

The initial random behaviour of the agents gradually became organized to produce obstacle avoidance as before. Following this, a large bold black arrow on a white card was held up in front of the moving camera pointing vertically up. The agent produced no particular response to the presence or absence of the card in the visual input, and thus we have the same situation as in Stage 1 of Pavlov's experiments (see **Figure 2**). Presentation of the upward pointing arrow and the button push, eliciting a move forwards reflex response, were then paired (made to co-occur while the agent remains in open space, i.e. it is not forced to crash) providing the agent with experience of the visual arrow input whilst moving forward, thus, mirroring the situation in Stage 2 of classical conditioning. Given experience of this pairing ( $\approx 2-5$  min,  $\approx 500$  to 1000 time steps) the agent was then able to consistently reproduce forward movement responses on presentation of the upward pointing arrow alone (without the additional hard wired button press). This produces Stage 3 of classical conditioning where the reflex response has been

successfully transferred to stimuli which previously elicited no discernable external response (see **Figure 2**).

The same method was repeated to condition a reverse (backward) response to a downward pointing arrow. Following a further 500 – 1000 time steps ( $\approx 2-5$  min) experiencing the pairing the agent was found to be differentially responsive to upward and downward pointing arrows producing either forward or backward motion respectively. The agent was then conditioned for left and right pointing arrows to produce left and right turns respectively. The agent could then be driven by remote control simply by holding the arrow up in front of the camera and turning it to point in one of the four conditioned directions. This is not only a demonstration of conditioned learning but also a demonstration of complex object recognition, in that the differences between an upward pointing arrow, and a downward pointing arrow, being both size and position variant are non trivial.

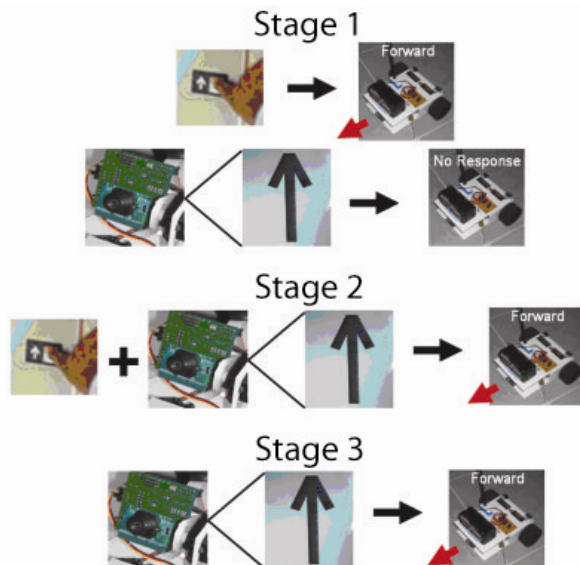


Figure 2: The three stages of Classical Conditioning. Stage 1: an unconditioned stimulus elicits an unconditioned response via a hard-wired reflex connection; the conditioned stimulus elicits no particular response. Stage 2, conditioned and unconditioned stimuli are repeatedly paired. In Stage 3, the conditioned stimulus now elicits the conditioned response independently of the reflex-response stimulus.

**Operant Conditioning.** In operant conditioning (Skinner, 1938), the consequences of any behavior can result in modifications to the production of that behavior. In the robot, this is demonstrated by changes in the behaviors leading to obstacle avoidance. Controlling the movement of the robot by presenting arrow stimuli to the camera, initially has the potential to cause collisions; however, on being ‘driven’ into obstacles the agent modifies its responses such that the remote control will eventually only work in situations where the visual ‘instruction’ will not cause a collision. If following the arrow is likely to cause a collision, the agent reverts to avoidance behaviors and then, once the collision has been avoided, the agent reverts back to the behavior associated with the presented arrow. This hierarchy of behaviour is not

unlike that produced by subsumption architectures (Brooks, 1989) in which more complex behaviours take over from simple behaviours; however, in this case the hierarchical ordering of behaviour is a product of experience rather than design.

## Discussion and Conclusion

As an integrated model, the DLA robot readily reproduces multiple psychological phenomena without requiring the imparting of task-specific knowledge from the designer. Rather, by learning the sensorimotor contingencies of its experience, the agent is subsequently able to direct its behavior in a manner informed by its past experiences. Although Noë claims that sensorimotor knowledge is not necessarily for the guiding of behavior, he readily admits that “the knowledge in question is practical knowledge; it is know-how. To perceive you must be in possession of *sensorimotor bodily skill*.” (Noë, 2004).

To recapitulate the conditioning experiments in enactive terms, the agent first experiences contingencies between active contact sensors and high valued infrared sensor values. Subsequently, rising infrared values from one side of the robot paired with moving in that direction produces the expectation of contact sensor activation. Although not part of Noë’s account, placing a negative value on these expectations can guide the robot’s behaviour away from such situations, promoting the selection of actions which have different expectations. This has been demonstrated on a real robot in a real untailored environment, i.e. not only in tidy robot arenas with high contrast obstacles but further in unstructured environments with hand held visual cues and noisy sensors. The presentation of visual stimuli in contingent relationships with the agent’s movements provides further opportunities for perceiving the world. The agent expects to see appropriately oriented arrows as it moves, or vice versa, to move in directions appropriate to the orientation of visually discriminated arrows. By Noë’s account, this is exactly the kind of knowledge required for enactive perception.

Following Newell’s (1973) suggestions for cognitive modeling, integration can be considered paramount to developing both cumulative models and theories. In the experiments briefly presented here (for further details see Morse, 2006) the focus has been on an embodied model of learning, therefore classical and operant conditioning were primary psychological targets, being archetypal theories of human and animal learning. Further to this, the inclusion of numerous other psychological features such as; semantic and repetition priming, overt and covert recognition, phobic acquisition, systematic desensitization, and sequence learning, all detailed in Morse (2006), demonstrates a level of integration rarely obtained by a single model. DLA is further argued to be both compatible with Noë’s account of enactive perception, and able to highlight difficulties in the application of such accounts, such as the problem of marginal regularities here addressed by the inclusion of a reservoir system.

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