Artificial Psychology Revisited: Constructs for Modeling Artificial Emotions

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Abstract - *Understanding the DNA of feelings and emotions are becoming increasingly important mechanisms for facilitating learning in intelligent systems. Here we present constructs for modeling human emotions within a foundation of artificial cognitive architectures[1] We model artificial neural emotions through the use of a weighted spatial-temporal emotional memory system, based upon knowledge relativity threads [2&3] human Autonomic Nervous System States. We artificially evolve the granularity of "emotional triggers" to determine importance thresholds which are context specific and relative to sensory inputs and environmental conditions to advance the capability of emotional learning and processing.*

We believe this has the potential to enhance artificial neural processing environments by allowing emotional memories and emotional learning to facilitate coalitions and cooperation between artificial neural intelligent software agents. We believe shared emotional states between intelligent software agents will more easily allow information sharing between agents, based on the "emotional reaction" to the systems sensory inputs, much in the way humans do.

Keywords: Artificial Emotions, Artificial Cognition, Artificial Psychology, Emotion Modeling

1. Introduction

For decades, psychological and psychiatric research has continued in parallel with the influx of advanced high performance computing and big data analytics architectures while early development has been undertaken into a hybrid fuzzy-neural processing architectures with an overarching objective to create genetic learning algorithms capable of human-like learning, reasoning and thought processing and, in particular, capable of learning about, processing, and utilizing emotions. Here we describe a modular architecture, based upon a mixture of neural structures and artificial connective neural tissue for evolving knowledge threads [2&11] within a system with weighted relativistic emotions to add flexibility and diversity to overall system capabilities. What we strive for is a continually adaptable neural processing system capable of dynamically adding and pruning basic building blocks of the neural system as the real-time environments (including emotional events) of the system change. The modular architecture artificial emotions architecture described here is based on fuzzy, genetic perceptron objects, called Cognitrons, The algorithms for which the Cognitrons are evolutionarily generated by the neural system or may be predetermined. The high-level artificial emotion architecture and information flow is illustrated in Figure 1.

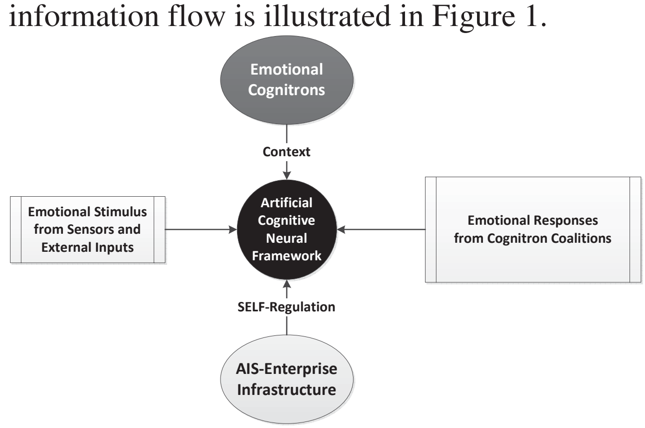

Figure 1 – Artificial Emotion High-Level Architecture

The purpose of this paper is to describe a neural framework for an Artificially Intelligent System (AIS) that provides "conscious" software agents; autonomous agents that range in functionality and are situated in the processing environment [7], allowing for development and use of emotions. Here we present structures within the AIS architecture required to provide artificial feelings and emotions and discuss the roles they can play. These agents would be actively involved in every instance of action selection, and at least potentially involved in each learning event. The pervasive, central role that feelings and emotions would play in the control structure of these conscious software agents mimics the roles they play in human cognition [8], and, over time, may give rise to clarifying hypotheses about human decision-making and several forms of human learning [1].

2. Descriptions of the Artificial Emotion Memory Components

In order to provide the AIS with emotional models, specialized roles for feelings in cognition, are created which all combine to produce motivations, actions and to facilitate emotional learning using artificially created and posited weighted stateful threads [2]. The various sorts of Cognitrons, perceptual, attentional, behavioral, and expectational, as well as their interactions will are described below:

1. ***Perception*** - Sensory stimuli, external or internal, are received and interpreted by perception creating meaning. Note that this stage is unconscious.
    a. **Early perception**: Input arrives through sensors. Specialized perception Cognitrons descend upon the input. Those that find features relevant to their specialty activate and broadcast their needs to the system. If perceptions are new and specialized perception Cognitron does not exist, then one is created followed by needs broadcasted.
    b. **Coalition perception**: Activation passes from Cognitron to Cognitron within the system. The Attention Manager brings about the convergence Cognitrons from different senses and into coalitions. *Pertinent thresholds of feeling/emotions are identified (recognized) along with objects and their relations by the perceptual memory system. This could entail simple reactive feelings based upon a single input or more complex feelings requiring the convergence of several different percepts; possibly defining an autonomic nervous system state* [9].
2. ***Perception to Preconscious Buffer***. Perception, including some of the data plus the meaning, is stored in preconscious buffers working memory [3]. These buffers may involve visuo-spatial, phonological, and other kinds of information. *Feelings/emotions are part of the preconscious perception written during each cognitive cycle into the preconscious working memory buffers. These buffers can be managed hierarchically or depth based upon time relevance to manage the storage or knowledge economy of the buffers.*
3. ***Local Associations***. Using incoming perception and nascent contents of the preconscious buffers as cues including weighted emotional threshold content, local Cognitron associations are automatically retrieved from transient episodic memory and from long-term associative memory. *Feelings/emotions are part of the cue that results in local associations from transient episodic and declarative memory. These local associations contain records of the agent's past feelings/emotions in associated situations*.
4. ***Competition for Consciousness***. Attention Cognitrons, whose job it is to bring relevant, urgent, or insistent events to consciousness, view short and long-term working memory. Some gather information, form coalitions and actively compete for access to consciousness.

Competition can include attention Cognitrons from a recent previous cycle. *Present and past weighted feelings/emotions thresholds influence the competition for consciousness in each cognitive cycle. Strong affective content strengthens a coalition's chances of rising to consciousness.*

5. ***Conscious Broadcast***. A coalition of Cognitrons, typically an attention Cognitron and its covey of related information Cognitrons carrying content, gains access to the system and has its contents broadcast. This broadcast is hypothesized to correspond to phenomenal consciousness. *The conscious broadcast contains the entire content of consciousness including the affective portions.* The contents of perceptual memory are updated in light of the current contents of consciousness, *including feelings/emotions*, as well as objects, and relations. *The stronger the affect, the stronger the encoding in memory.* Transient episodic memory is updated with the current contents of consciousness, *including feelings/emotions*, as events. *The stronger the affect, the stronger the encoding in memory.* (At recurring times not part of a cognitive cycle, the contents of transient episodic memory are consolidated into long-term declarative memory.) Procedural memory (recent actions) is updated (reinforced) with the strength of the reinforcement influenced by the strength of the affect.
6. ***Recruitment of Resources***. Relevant behavioral Cognitrons respond to the conscious broadcast. These are typically Cognitrons whose variables can be bound from information in the conscious broadcast [4]. If the successful attention Cognitron was an expectation Cognitron calling attention to an unexpected result from a previous action, the responding Cognitron may be those that can help to rectify the unexpected situation. This is known as Cognitronic stochastic diffusion where importance thresholds per each impending need are dynamically processed. Thus artificial consciousness moves towards solving the relevancy problem in recruiting resources. *The affective content (feelings/emotions) together with the cognitive content help to attract relevant resources (processors, neural assemblies) with which to deal with the current situation.*
7. ***Action Chosen***. The behavior subsystem chooses a single behavior (goal context), perhaps from a just instantiated behavior stream or possibly from a previously active stream. *This selection is heavily influenced by activation passed to various behaviors influenced by the various feelings/emotions*. The choice is also affected by the current situation, external and internal conditions, by the relationship between the behaviors, and by the residual activation values of various behaviors.
8. ***Action Taken***. The execution of a behavior (goal context) results in the behavior Cognitrons performing their specialized tasks, which may have external or internal consequences. The acting Cognitrons also include an expectation Cognitron whose task it is to monitor the action and to try and bring to consciousness any failure in the expected results.

Figure 2 illustrates the AIS emotional trigger development that comes from steps 1-8, which includes a fuzzy inference engine that utilizes past behaviors and current circumstances to derive the emotional triggers.

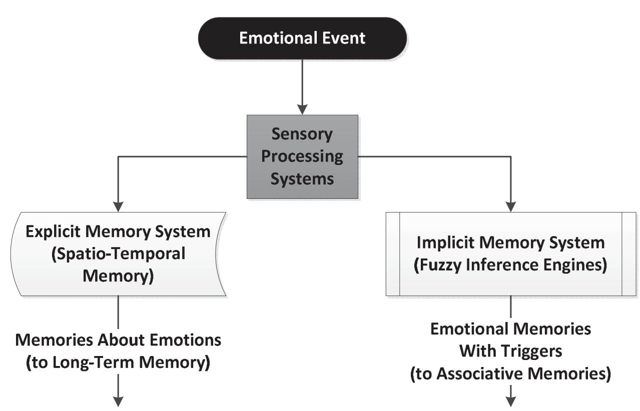

Figure 2 – Emotional Trigger Development

In humans, it is expected that the cycle of steps 1-8 happens 5-10 times a second, overlapping, with some happening in parallel [2].

3. Emotional Learning

Figure 3 illustrates the basic emotional learning architecture for the AIS. The genetic learning agents inherit initial states from the memory system and inherit the initial parameters for behavior from the behavioral center of the AIS. The consciousness mechanism, along with the mediator, controls the response of the learning agent, and direct its constraints based on the environment and the problems to be solved currently. This provides the priorities, preferences, goals, needs, and activation constraints (when you know you've learned something). The genetic agents (called genomes) adapt to the environment and gather information in order to make conclusions (learn) about the problem to be solved [13].

In the genetic environment, genomes are transferred to other agents, in order to speed up the adaptation of new generations of conscious agents in the behavioral environment. In the AIS, drives, priorities, and constraints influence emotions. The behavioral subsystem receives situations and computes actions, while memories provide personality parameters and the various conscious agents' sensitivities to emotional computation. We can think of the cross-connectivity of the neural layers as a matrix, and can compute emotional response from the column-wise fuzzy weightings, and the action response from the row-wise fuzzy weightings.

It is assumed that each matrix element E_{aj} represents an emotion. *Emotion* (a, j) of performing action *a,* in situation *j*. Given this, the genetic learning agents perform an emotion learning procedure, which has four steps [10]:

1. State *j*: choose an action in situation – (let it be action *a*; let the environment return situation *k*).
2. State *k*: feel the emotion for state *k* – *emotion* (*k*).
3. State *k*: learn the emotion for a in *j* – *emotion* (*a, j*).
4. Change state: *j* = *k*; return to 1.

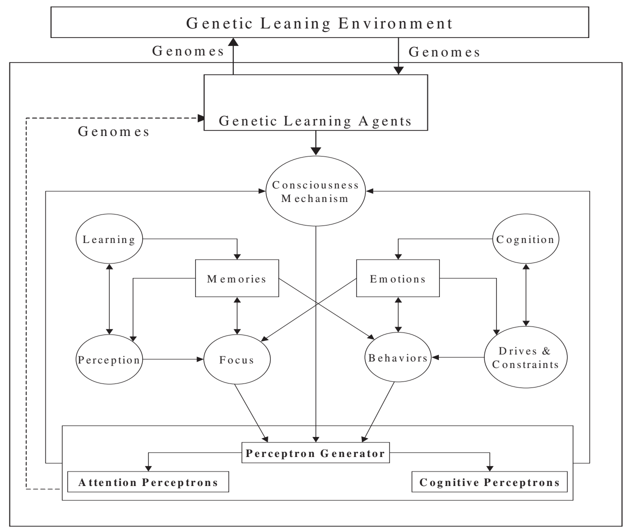

Figure 3 – Genetic Emotional Learning Architecture

This learning procedure is an emotion secondary reinforcement learning procedure. The learning constraint used in step 3 is:

$Emotion^0\ (a, j)$ = genome^0 (inherited)

$Emotion^1\ (a, j) = Emotion^0\ (a, j) + emotion\ (k)$

This learning rule adds the emotion of being in the consequence situation, *k*, to the emotion toward performing action *a* in situation *j* on which *k* is the consequence. This drives us to define an ontology for each action driven by an emotional response for our AIS. Figure 4 illustrates this Cognitron Emotional Response Ontology.

4. Discussion: Human vs. Artificial Emotions

Many researchers have postulated that human cognition is implemented by a multitude of relatively small, special purpose processes, almost always unconscious communication between them is rare and over a narrow bandwidth. Experiments have shown that humans make judgments about the degree of resemblance to meaningful representations or prototypes during classification and identification of content; robins are judged as more prototypical birds than penguins [14]. Hence, the existence of gradients within concepts or what is known as continuous perception [15] Coalitions of such gradient processes find their way into consciousness. This limited capacity workspace of our cognition serves to broadcast the message of the coalition to all the unconscious processors, in order to recruit other processors to join in handling the current novel situation, or in solving the current problem. Thus consciousness in this theory allows us to deal with novelty or problematic situations that can't be dealt with efficiently, or at all, by habituated unconscious processes. In particular, it provides access to appropriately useful resources, thereby solving the relevance problem [9].

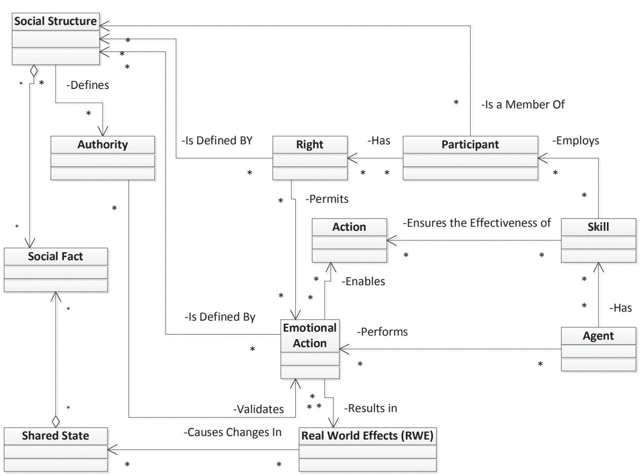

Figure 4 – Emotional Cognitron Action Ontology

All this takes place under the auspices of contexts: goal contexts, perceptual contexts, conceptual contexts, and/or cultural contexts. These may look like goal hierarchies, dominant goal contexts, a dominant goal hierarchy, dominant context hierarchies, and lower level context hierarchies. Each context is, itself a coalition of processes. Though contexts are typically unconscious, they strongly influence conscious processes [5].

Baars [4] postulates that learning results simply from conscious attention, that is, that consciousness is sufficient for learning. There's much more to the theory, including attention, action selection, emotion, voluntary action, meta-cognition and a sense of self. It can be seen as a high level theory of cognition.

The AIS emotional cognitive processing model suggests that software agents and robots can be designed to use feelings/emotions to implement motivations, offering a range of flexible, adaptive possibilities not available to the usual more tightly structured motivational schemes such as causal implementation, or explicit drives and/or desires/intentions [6].

So, what can we conclude? Explicit drives seem likely to suffice for quite flexible action selection in artificial agents. It is expected that feelings and emotions will be required in agent architectures requiring sophisticated learning. Specifically, it is expected that artificial feelings and emotions can be expected to be of most use in software agents or robots in which online learning of facts and/or skills is of prime importance. If this requirement were present, it would make sense to also implement primary motivations by artificial feelings and emotions.

References

1. Crowder, James A., John N. Carbone, and Shelli A. Friess. Artificial Cognition Architectures. Springer, 2014.
2. Carbone, J. "A Framework for Enhancing Transdisciplinary Research Knowledge." Texas Tech University (2010).
3. Crowder, James A., and John N. Carbone. "Eliminating Cognitive Ambiguity with Knowledge Relativity Threads."
4. Ackley, D. and Litman, M. 2002. Interactions between Learning and Evolution. Artificial Life XII. Addison-Wesley.
5. Anderson, J. 2004. Cognitive psychology and its implications: John r. Anderson: Worth Pub.

6. Ashcraft, M. 1994. Human Memory and Cognition. Harpercollins College Division, New York, NY.
7. Baars B. 1988. A Cognitive Theory of Consciousness. Cambridge University Press, New York.
8. Crowder, J. 2010. Flexible Object Architectures for Hybrid Neural Processing Systems. Proceedings of the 12th annual International Conference on Artificial Intelligence, Las Vegas, NV.
9. Crowder, J. 2012. Cognitive System Management: The Polymorphic, Evolutionary, Neural Learning and Processing Environment (PENLPE). Proceedings for the AIAA Infotech@Aerospace 2012 Conference, Garden Grove, CA.
10. Crowder, J. 2012. The Artificial Cognitive Neural Framework. Proceedings for the AIAA Infotech@Aerospace 2012 Conference, Garden Grove, CA.
11. Crowder, J. and Carbone, J. 2011. The Great Migration: Information to Knowledge using Cognition-Based Frameworks. Springer Science, New York, NY.
12. Crowder, J. and Friess, S. 2012. Artificial Psychology: The Psychology of AI. Proceedings of the 3rd Annual International Multi-Conference on Informatics and Cybernetics. Orlando, FL.
13. Crowder, J. 2014. Psychological Constructs for AI Systems: The Information Continuum. Proceedings of the 16th annual International Conference on Artificial Intelligence, Las Vegas, NV.
14. [Harnad, 1987] Harnad, S., Categorical Perception: The Groundwork of Cognition, Cambridge University Press.
15. Gärdenfors, Peter, and Mary-Anne Williams. "Reasoning about categories in conceptual spaces." IJCAI. 2001.