

Anticipative Emergence in Environment Virtual

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Abstract. This paper describes how a group of agents can anticipate the possible changes within a virtual environment, than this concept the actors explore and adapts to the environment, thanks to mechanisms of evolution and adaptation, that provide the genetic algorithms and the classifier systems, with this capacity to learning and take one action by resolve a problem or change his objectives. The main idea of the anticipation is based on the acquisition of knowledge of events happened in the environment of the past, later to compare them with the actions that appear in the present, in a time specify. The events of the past to like learning and make the calculus and the interpolating with the actions that happen in the present, this way to be able to make all the calculations necessary to be able to anticipate the possible changes in the environment [Hoffmann, J (1993)].

Keywords: Adaptation, Agents, Anticipation, Classifier System, Intelligence Artificiel.

1 Introduction

The main idea of the anticipation is base on the capacity to predict changes in the environment, that allow developed one new condition many favorable. One approach to designing intelligent agents systems is to look to the different studies in the biological systems for clues and design principles. The result is a system that builds an environmental model that applies reinforcement learning techniques. The main learning mechanism of the agents is a classifieur (CS) that introduce a genetic algorithm (GA). However, recently the concept of anticipations need more techniques in artificial learning systems, because is necessities implementer the aspects the learning cognitive. Inside the world of artificial and evolutionary learning systems to allow incorporate techniques based to fitness to the eXtended Classifier System (XCS), or Learning Classifier System (LCS) [Wilson, 1995] the accuracy-based approach in XCS over comes the previously encountered problems in LCSs where especially deferred reward lead to over-generalization and unequal distribution of classifiers in the problem space [Wilson, 1989]. Moreover, XCS solves the problem of speciation and what mating restriction schemes should be used implicitly by the accuracy measure combined with genetic algorithm (GA).

2 The Anticipatory Classifier System (ACS)

The ACS [Stolzmann, 1998] has its origins in LCSs and cognitive psychology. The framework of the ACS shows many similarities with LCSs. Differences can be de-

tected in the enhanced classifier structure as well as the application of the learning process. For explain with work this type of system; we start with the environment interaction. The ACS interacts autonomously with an environment. In the behavioral act at certain time t , it perceives a situation $\sigma(t) \in I = \{t_1, t_2, \dots, t_m\}^L$ where m is the number of possible values of each attribute and L is the string length, is not necessarily coded binary but can only take discrete values. The system can act upon the environment with an action $\alpha(t) \in A = \{\alpha_1, \alpha_2, \dots, \alpha_n\}$ where n specifies the number of different possible actions in the environment and $\alpha_1, \dots, \alpha_n$ are the different possible actions. Note, after the execution of an action, the environment provides a scalar reward $\rho(t) \in R$.

2.1 Knowledge Representation

The knowledge in the ACS is represented by a population $[P]$ of classifiers. Each classifier represents a condition action anticipation rule having the following components:

- The condition part (C) specifies the set of input situations in which the classifier can be applied.
- The action part (A) proposes the classifier's action.
- The effect part (E) anticipates the effects that the classifier believes to be caused by the specified action.
- The mark (M) records all values in each attribute of the classifier that do not anticipate correctly sometimes.
- The quality (q) measures the accuracy of the anticipations;
- The reward prediction (r) predicts the reward expected the execution of action A.

The condition and effect part consist of the values perceived from the environment and '#' symbols (i.e. $C, E \in \{t_1, t_2, \dots, t_m, \#\}^L$). A # symbol in the condition called don't care symbol means that the classifier matches any value in this attribute. However, a # symbol in the effect part called pass through symbol means that the classifier anticipates that the value of this attribute won't change after the execution of specified action A. An action can be any action possible in the environment. The mark has the structure $M = (m_1, \dots, m_l)$ with $m_i \subseteq \{t_1, \dots, t_m\}$. The measures q and r are two scalar values where $q \in [0, 1]$ and $r \in R$. A classifier with quality greater than the threshold θ_r is called reliable and becomes part of the internal environmental model. A classifier with a quality g lower that the threshold θ_i is considered as inadequate and is consequently deleted. All these parts are modified according to de reinforcement learning mechanism.

2.2 Reinforcement Learning

In XCS, the reinforcement learning approach adapts the Q-learning idea in reinforcement learning [Watkins, Dayan, 1992]. A first mathematical analysis of Q-learning in generalizing systems such as LCSs can be found in [Lanzi, 2002] In order to learn an optimal policy en the ACS, the reward prediction r of each classifier in an action set is updated. For the reliability of the maximal Q-value in the successive state, we con-

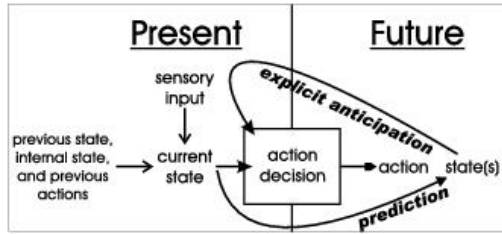


Fig. 1. Decision by predictions about the future

consider the quality of the classifier assuming that the reward converges in common with the accuracy of the anticipation. Once an accurate, reward sufficient model of the environment is evolved, the update method converges to the Q-learning theory and the formation of an optimal policy is assured.

$$r = r + b_r * (\rho(t) + \gamma^*) \max_{cl \in [M]} (q_{cl} * r_{cl}) - r$$

The parameter $b_r \in [0, 1]$ denotes the reward learning rate and $\gamma \in [0, 1]$ the discount factor similar to Q-learning.

2.3 The Anticipatory Learning Process (ALP)

The ALP is derived from the psychological learning theory of anticipatory behavioral control [Hoffmann, 1993]. While the similarity with the learning theory is discussed elsewhere [Stolzmann, Butz, Hoffmann & Goldberg, 2000]. The ALP compares the anticipation of each classifier in an action set with the real next situation. According to this comparison and the current structure of the classifier, the classifier is modified and new classifier may be generated.

3 Prototype Model

This prototype simulates an environment in which two different agents that both exhibit realistic natural behaviors can be placed. The entire agent will have rules that will apply to them as individuals (i.e. local rules), [Reynolds, 1987], and each of the agent will change their objectives with regard to environment.

The objective of this prototype system is to show emergent and anticipated the actions complex global behavior this complex global behavior will emerge from the interactions of moderately simple local rules.

Emergence is an essential aspect of Artificial Life, as was stated by [Langton, 1989]. “Artificial Life is concerned with tuning the behaviors of such low-level machines that the behavior that emerges at the global level is essentially the same as some behavior exhibited by a natural living system. Artificial Life is concerned with generating lifelike behavior.” Emergence can lead to *self-organizing behavior*, which means the spontaneous formation of well-organized structures, patterns, or behaviors,

from random initial conditions. The behavior of interest is often found in the area between order and chaos, which could be described as *organized complexity*.

These ideas are based on natural living systems, where dynamical structures are not devised to exhibit this behavior, but they develop it spontaneously from random initial conditions. The theory is that in nature there is a tendency for spontaneous self-organization, which is universal, [Kauffman, 1993]. This process of self-organization can also be interpreted as the evolution of order from chaos.

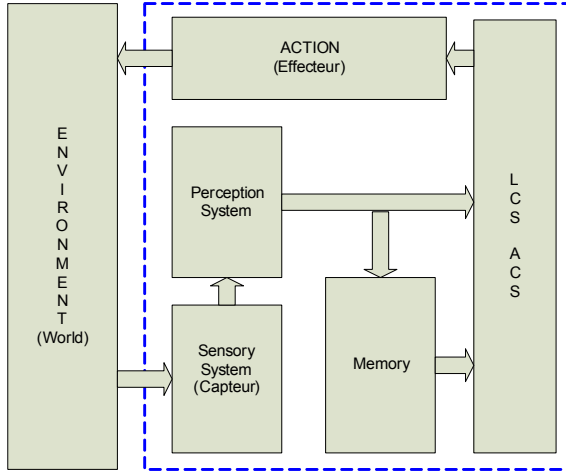


Fig. 2. Virtual behavior Framework

3.1 The Environment

A formal abstraction exists between the agent and the world. The world model's primary function maintains the list of agents and objects and to act as an event black-board for the posting and distribution of the world events. It also coordinates network synchronization and manages rendering.

World events take the form of data records, perceptual nuggets than can be processed by an agents sensory and perception systems.

3.2 Sensory System

The sensory system is a filter though which all world events must pass. Unlike its physical equivalent, where any data that passes through is fair game, the sensory system plays an active role in keeping the virtual agents. In a simulated world, there is potentially much more accessible information that the agent, limited by its sensory module, should be able to sense. For example inside in world of species carnivores, herbivores, the carnivores can locate the herbivores that are behind him, he shouldn't be given it. While often the role of the sensory system is to filter out data that cannot be sensed [Sanchez, E. 2003], other times its role is to transform it. It converts visual location information in to local space of the sensing an object or identify other agent in the environment. The agent receives all local information from the world.

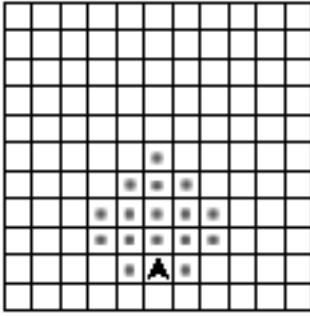


Fig. 3. Map of perception of agent



Fig. 4. Agent in environment virtual

3.3 Perception System

Once the stimulus from the world has been sensed it can then be perceived. The distinction between sensing and perceiving is important. An agent may sense an event but it is up to the perception system to recognize a process the event as something that has meaning to the agent. Thus, it is within the perception system that meaning is assigned to events in the world. The perception system takes the form of a percept tree. A percept tree is an atomic classification and data extraction unit models some aspect of the sensory it returns both a match probability, the probability represents the experience.

3.4 Memory

Memory is a repository for the events that pass in the environment. The memory is itself a useful structure by caching together the various perceptual impressions made by a world event, to the decision making, the agent's status system monitor and stores internal states of the virtual actor in order to simulate its knowledge of its actual situations. The memory provides of the world can be informed by more just direct perception. Much like our own perception where unobserved data is subconsciously by low-level prediction an assumption, agents implemented under the framework can be designed to act upon events that are like to have. We believe that the ability to recognize temporal patterns and act on them is an essential component of common sense intelligence. Sometimes prediction is used not to predict the future but simply to maintain a coherent view of the present. The stream of sensory data coming from object is out of the agent's visual field, or because it is occluded by another object. In these cases, prediction can allow in agent to maintain a reasonable estimate of where the object is even though it is not being observed. The actual mechanisms of prediction can take many forms. What objects contain histories of percept data are vector or scalar, to use function approximation techniques to extrapolate values. These mechanisms of prediction could conceivably extend to common sense knowledge about the world if an object is suspended with no visible support, it might be predicted to fall. The occasional deviation of predictions from the actual state of the world and the magnitude of that deviation also provide a basis for anticipate or surprise, a surprising is an excellent method for focusing perception.

4 Anticipation

Consider that for each agent, for each state, and at each time, there is a computable values for the probability that active agent could successfully collaborate with passive agent. As the world constantly changing, the values for the probability of collaboration are computed as a function of the dynamic world. Assuming that the transition between states for each agent take time or other type cost, then anticipation consists of the selection of a new state that maximizes the probability of future collaboration. Anticipation therefore allows for a flexible adjustment of team agent towards the increase of the probability of being useful for team.

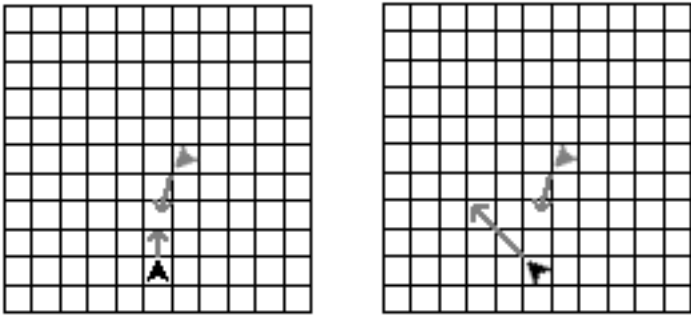


Fig. 5. Anticipation of collision of the agents

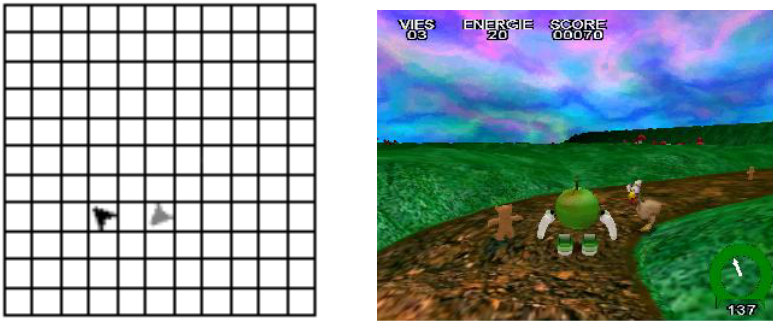


Fig. 6. Agents in the environment virtual

5 Conclusion

In this paper, we described several LCSs, each of the then casting a new light on the concept of generalization in the LCS framework. In particular, we enlighten how most LCS like XCS consider generalization with respect to an expect payoff, while other LCS like ACS consider it with respect to anticipated effects in terms of situations. We also enlighten some limitation of the formalism of ACS. A lot of future research is needed to understand exactly when and which anticipation is useful or sometimes even mandatory in an environment to yield competent adaptive behavior. Although psychological research proves that anticipations take place in at least higher animals, a clear understanding of the how, the when, and which is not available. Any system of

agents system requires some coordination of action. Thus, one essential direction of future research is to identify environmental characteristics in which distinct anticipatory mechanism are helpful or necessary.

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