Metacognition, Agents, Animats and the Society of Minds

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Abstract

This paper presents the initial results in the design of a society of agents using the concept of optimal qualities of animal cognition. The main purpose of this research paper is to understand the principles of natural minds and adopt these principles to simulate artificial minds. These approaches necessarily require the design, testing and computational analysis of both simple and complex agents. The developing BDI (Belief, Desire Intention) society model is tested using agents in a fungus world. Drawing on qualities found in natural minds, the aim is develop a self configurable computational model using the concept of metacognition. Qualities investigated include physiological and goal oriented behaviour, the conceptual level associated with decision making and its cost function and utility behaviour at the microeconomic level.

1 Introduction

This research paper addresses the following questions.

- What is mind and are artificial minds possible?
- What are the principles of artificial minds?
- What are the commonalities between natural and artificial minds?
- How to simulate qualities of natural minds?
- Why the need to simulate artificial minds?
- How can we develop better and more sophisticated agents to simulate qualities of natural agents (animals) in artificial minds?
- What is metacognition? Is it necessary? What is the effect on results for agents with metacognition?
- How can the distributed model of society of agents (Minsky, 1985) approach lead to metacontrol and metacognition mechanisms?

The above key questions are raised with the intention of providing solutions or at least some steps or progress towards answers. These questions fit with the academic disciplines of Artificial Intelligence and Cognitive Science.

Artificial Intelligence originated with the desire to develop artificial minds capable of performing tasks with human and non human-level ability. It has developed in number of directions including intelligent systems, reasoning and knowledge representation and robotics. Cognitive Science originated in the desire to integrate expertise in the traditionally separate disciplines of computer science, psychology and philosophy, in order to advance our insight into cognitive tasks like problem solving, decision making, language, memory and learning.

One perspective on how to do this is to develop cognitive architectures. These cognitive architectures are also called artificial mind models. Cognitive architectures are designed to be capable of performing certain behaviours and functions based on our understanding of human and non human minds. Important issues in developing cognitive architectures include task effectiveness, goal achievement, and the ability to perform well in novel situations. Examples of developed cognitive architectures include SOAR [14], ACT-R [2], CRIBB [3], EM-ONE [17], CogAff [18] and CAMAL [6]. CAMAL is a theoretical framework developed from ideas incorporated in the CogAff, CRIBB, Guardian [10], EM-ONE [17] and Minsky [12] architectures.

Any cognitive or intelligent or robotic architecture can be viewed as a single agent or a large collection of agents. The collection of agents approach allows each (micro-) agent to be used as a different way to represent and reason with knowledge, with (micro-) agents specialized for some type of knowledge or cognitive process.

Metacognition [1, 7] is a relatively new area in cognitive theory. Metacognition is defined as thinking about thinking. It can be viewed as two, simultaneously occurring, processes: monitoring a group of agents in an intelligent or cognitive or robotic architecture (i.e. self reflection); and making changes and adapting effective strategies in that group of agents (Meta-control). Hence, metacontrol is one part of metacognition.

Testbeds and benchmarks [9] are mainly used for simulating and comparing architectures and outcomes in the field of robotics or cognitive architectures. The fungus world environment [21] allows the principles and behaviours of a robot or simulated animal or any artificial mind simulation to be monitored, measured and compared. Pfeiffer [15] describes the fungus eater concept as a testbed for simulating models in emotion psychology.

1.1 Definition of Mind

Minsky [12] says "*Minds are just what brains do*". Franklin [8] argues that the foundation of exploring a mechanism of mind can be done through the possibility of artificial minds. The implemented artificial minds are man-made systems that exhibit behavioural and characteristics of natural living or natural minds.

1.2 Reasons for Studying Artificial Minds

Why do we need to study artificial minds? What is the need for studying non-human minds such as animals or robots? In "Artificial Minds", Franklin [8] gave three important reasons for studying artificial minds.

- Questions related to the nature of intelligence (human and nonhuman minds) are inherently fascinating. The research on artificial minds may well throw lights on their questions.
- To better understand upcoming man machine mechanisms (artificial models or cognitive architectures)
- To build robots or intelligent machines (possibly artificial models or cognitive architectures) and to deal with them effectively.

1.3 Principles of Natural Minds

Animal cognition [11, 21] is defined as the mental process, or activity, or mental capabilities of an animal. It includes the acquisition, storage, retrieval, and usage of the knowledge. This has been developed from different disciplines like ethnology, behavioural ecology, and evolutionary psychology. Animal psychology includes experiments on the intelligence of animals. This is the simplest form of exploring the complex behaviour of human beings. Most cognitive scientists are interested in comparing human cognition with machine cognitions, others are interested in animal cognition.

The common biological origin of animal and human cognition suggests that there is a great resemblance in animal and human cognition, greater than the resemblance between machine and human cognition. Animal cognition is similar to human cognition, and follows, more or less, human cognitive psychology.

According to Berger [4], animals are both like and unlike humans. Children sometimes behave like animals, through a reflexive way. Examples include feeding and training children, or taking them to bed, and so on.

1.3.1 Laws on Animal Behaviours

The behavior of an animal has consequences which depend on situation [11]. The important consequence of behavior is energy expenditure. Energy and other physiological commodities such as water, weather etc. Such expenditure must be taken into account, because it influences the animal state. According to Thorndike [20] the behaviour of animal intelligence is predictable and follows the uniformity of nature. He says that "any mind will produce the same effect, when it is in the same situation." Similarly, an animal produces the same response, and if the same response is produced on two occasions, the animal must have changed. The law of instinct or original behaviour is that an animal in any situation, apart from learning, responds by its inherited nature of its perception in its action and connection moves [4].

1.3.2 Decision Variables

A decision of a person, animal or robot is simply the activity whereby decision variables are compared to decision boundaries. From the economic point of view, the decision-making unit is called the cost or performance. Decision-making with respect to use of a cost and utility function depends on given thresholds, decision variables and decision boundaries [11].

1.3.3 Cost and Utility Function

The decision making level in animals is defined in terms of cost functions and utility behaviors - the microeconomic level. Cost functions and utility behavior in animals operate in such a way that a utility (for example, energy) is maximized or minimized [11].

1.3.4 Learning in Animals

Learning is a part of development. It is a result of adaptation to accidental or uncertain circumstance. When the animal learns environmental situations, it undergoes permanent change. We expect that learning should, in general, bring beneficial results. Animal learning is similar to reinforcement learning in machine learning or robotics [11, 13, 19, 23].

1.3.5 Intelligent or Optimal Behaviour

Animal behaviour is a tradeoff between the native courses of action, i.e. physiological, and goal oriented behaviour. An animal engaged with activities optimizes its pattern of behaviour with respect to the use of energy and time. For example the optimal behaviour of a hungry pigeon faced with a source of food is to eat. The animals engage activities in order to optimize its pattern of behaviour with respect to the use of energy and time. If the conditions are relevant to two or more activities simultaneously, it chooses the most optimal action among them in terms of its innate and learnt decision boundaries [11].

2 Metacognition

The study of metacognition has grown since the 1970s. In educational psychology, Flavel [7] and others developed a model of children's cognition about a memory (metamemory), understanding (meta-comphrension) and communication (meta-communication). Metacognition is often simply defined as "thinking about thinking" [22]. Broadly defined, metacognition is any knowledge or cognitive process that refers to monitoring and controlling any aspect of cognition.

According to Adkins [1] metacognition is thinking about knowing, learning about thinking, control of learning, knowing about knowing, and thinking about thinking. Minsky [12] states that we cannot think about thinking, without thinking about thinking about something. Where that something is a behaviour or activity, the metacognitive act can be referred to as metacontrol.

According to Flavel, there are three stages in metacognition: (1) metacognitive knowledge; (2) metacognitive experience; and (3) metacognitive regulation. Metacognitive knowledge contains a database of knowing about an environment, the nature of the task, and strategies used for knowing the facts. Metacognitive experience is, after processing, a given task, getting knowledge, or results. Controlling and (the self reflective) monitoring of progress using cognitive tasks is termed metacognitive regulation.

3 Society of Artificial Minds

There are different classifications of agents, by different researchers in both formal and informal ways. The purpose of this research is to understand principles of natural minds (animals) and adopt these main principles to the design of artificial minds. This broad approach necessasarily requires designing different computational agents, both simple and complex. Wherever possible simple agents (or animats or micro-agents) are used to model specific micro-economic activities. Different skill levels are implemented as individual agents of differing types. Where mico-agents can be combined complex skills can be achieved using the society of mind approach.

The society of artificial minds is coordinated using deliberative agents. A deliberative agent describes its actions through an explanation based on its beliefs and desires. Beliefs can be derived from perceptions and previously held beliefs. Motivational states [6] are defined on the basis of Belief, Desire and Intention models. The optimal agents maintain its optimal motivational state to perform its actions upon the environment. Some of the fungus world BDI models are given below.

3.1 Experimental Setup

This Fungus world testbed is implemented using SWI-Prolog. The fungus world testbed in this experiment includes cognitive and engineering perspectives. The fungus world environment has been created to have dynamic and static entities. Static entities blocks are used to create a particular location within the environment. There are different parameters in the environment for the testing of an agent's biochemical engine and performance. These include the presence and amount of standard fungus, small fungus, bad fungus, ore, golden ore and medicine.

3.2 Different Agents in the Experiment

Different types of agents (Random, Reflexive, Reactive, Reflexive-Learner and BDI-model) are introduced in this experiment. Each type of agent differs in their actions and behavior traits (from simple to complex). All agents move in the environment, changing direction in case of obstacles. To compare the results of each agent, the following statistics were collected: life expectancy; fungus consumption (including the standard fungus, small fungus and bad fungus); resource (standard and golden ore) collection; and metabolism. The life expectancy is noted through agents expiring before the maximum experiment cycles. Total performance is denoted by the combination of resource collected and life expectancy.

3.2.1 Random

This type of agent moves randomly. It checks the corresponding adjacent positions and determines the random direction either up, down, left or right.

3.2.2 Reflexive

Reflexive agents are simple, instinctual types (fixed way of behaving to particular stimuli). They do not have any explicit motivational states like belief, desire, and intentions. Reflexive agents understand their environment sensors and in terms of the following Finite State Machine examples.

I. Reflexive 1

Uses FSM and Up|Left|Right|Down

Prefers move > nothing

Prefers up | left| right | down (arbitrary order)

II. Reflexive 1.a (2nd condition):-

Uses FSM and Up|Left|Right|Down

Prefers move > nothing

Prefers Random direction.

III. Reflexive 1.b (3rd condition):-

Uses FSM X Up|Left|Right|Down

Prefers move nothing

Prefers move towards environment centre.

IV. Reflexive 1.c (4th condition):-

Uses FSM X Up|Left|Right|Down

Prefers move over nothing

Prefers move towards edge of the environment.

3.2.3 Q-learner (learner)

Q-learning algorithms work by estimating the values of state-action pairs. The value Q(s,a) is defined to be the expected discounted sum of future payoffs obtained by taking action a from state s and following an optimal policy (i.e. delta value to find Q values) from the current state s, selecting an action a. This will cause receipt of an immediate goal unit and arrival at a next move.

The reinforcement learning (RL) algorithm mainly started in the 1980s, in relation to the psychology of animals. RL has become more popular recently due to its good performance, especially in the areas of machine learning and artificial intelligence [16]. Reinforcement learning focuses on decisions that people and animals face in their everyday normal lives, estimating state-transition probabilities and expected immediate rewards of the environment. This algorithm is the problem faced by the agent in the environment to learn through trail and error interactions. Reinforcement learning is a learning, planning, and action selection paradigm based on maximizing reward [13, 19].

Q-Learning Algorithm

Let **Q**(s,a) be the expected discount of reinforcement of taking action a in state s, then continue by choosing actions optimally [13,19].

1. Initialise a table **f** with states **S**, actions **A** and the **Q** (utility or reward) value estimates.

2. Select an action a (where $a \in$ **A**) and execute it.

3. Observe the immediate reward r. Reward is defined using some agent relation, for example distance to desired object. Observe the new state s', achieved by action a on state s, where $a \in$ **A** and $s \in$ **S**.

4. Update the table entry for **Q** value using an appropriate rule, for example

New **Q**(s, a) = Old **Q**(s, a) + ($r(s) - r(s')$)/ $r(s)$.

The **Q** values converged to their optimal values

5. Update the state: $s' \rightarrow s$.

3.2.4 BDI agents

BDI agents have the ability to supervise their own status (i.e. energy level and metabolism), and they can change or update their aims (towards ore, fungus or medicine) by making optimal decisions and thus achieve their goals. It can be argued that this is one form of self-reflection; over reactive processes. Extending this concept, reflective processes with learning capabilities can lead to metacontrol and metacognition mechanisms.

Basic Belief-Desire-Intention Model.

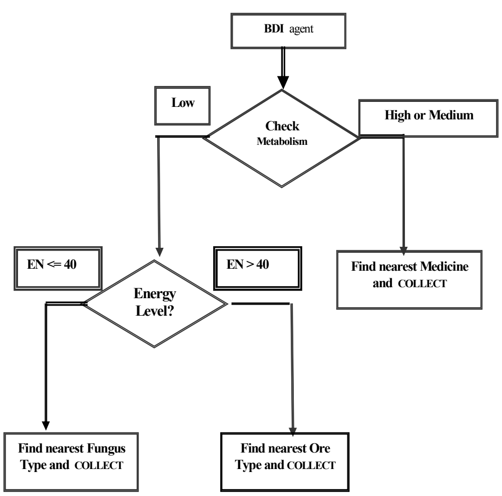

Fig 1. BDI Agent.

(1) Metabolism > Low,

Searches for the nearest medicine to collect in order to lower the metabolism by through Reactive mechanisms.

(2) Energy Level <= Decision variable

The agent desires to move towards fungus in order to avoid the hunger condition or their death (Physiological oriented). Uses the Reactive Fungus FSM and Up|Left|Right|Down to find the nearest Fungus, and select the direction towards that fungus

(3) Energy Level > Decision variable

Reactive Ore (Goal based behaviour move towards nearest Resource) Uses FSM and Up|Left|Right|Down

Find the nearest ore (Included ore, Golden ore). Select the direction towards that ore.

4 Simulation Results

Experiments were conducted separately for each type of agent. In order to compare results in the experiment, the same statistics were collected. Four types of agents were employed for these experiments.

4.1 Ore Collection

The collection of standard ore and golden ore by agents Random, Reflexive, Learner, and BDI-model agents are as follows: Random agents collects 16% of ore, Reflexive agents collects 26% of ore, Learner agents collects 57% of ore and BDI-model agent collects 80% of ore.

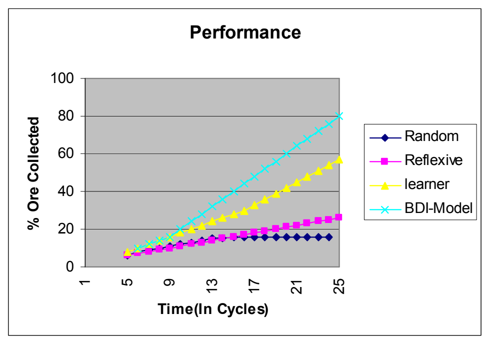

Fig 2. Amount of ore collected by different agents.

4.2 Life Expectancy

Energy level of each type of agent is noted after the maximum cycles.i.e agent's energy left after the end of maximum cycles.i.e Random agents died in the 24th life cycle, because of lack energy. Reflexive agents are managed 16% of energy, Learner agents left 52% of energy and BDI agents are left 73% of energy.

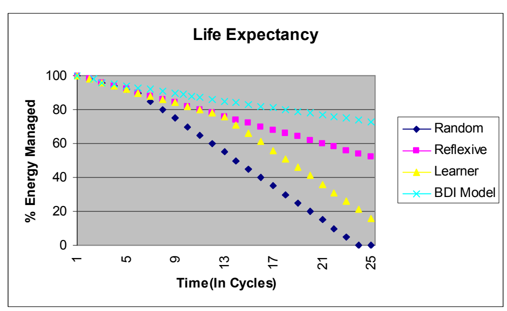

Fig 3. Life expectancy of different types of agents.

4.3 Analysis and Conclusion

Based on the results obtained in this experiment, the life expectancy and the ore collection of BDI-model agent are higher than Random, Reflexive, and Learner agents. The level of decision-making in BDI-model agent demonstrated from the experimental results that the BDI-model agent's cost function and utility maintenance is optimal (of ant of the agents tested). The energy spent (maximum cycles with low metabolism) in each move of BDI-model agents is minimal or minimized (due to maintenance of low metabolism), and collecting ore also maximizes utility.

In all, agents have around more than 50 behaviours. The results demonstrate simple, moderate and complex behaviour in a society of agents.

The BDI models are designed to demonstrate how the metacontrol and metacognition mechanisms can be applied on the different models (Thinking of energy, thinking of metabolism, thinking of their goals, according to their self-reflection or internal conditions). The BDI-model agents engaged with activities optimize their patterns of behavior with respect to the use of energy and time. The level of decision making switches into fungus consumption when they are hungry (lesser than decision making energy level), and if they are normal, switches to goal-oriented (i.e. collection of ore), which demonstrates the physiological and goal-oriented behavior.

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