

# METACOGNITION IN A “SOCIETY OF MIND”.

Vijayakumar M V and Darryl N Davis

Department of Computer Science, University of HULL,  
United Kingdom,

[www.net.dcs.hull.ac.uk/NEAT](http://www.net.dcs.hull.ac.uk/NEAT)

{[V.Maragal.Venkatamuni@2004.hull.ac.uk](mailto:V.Maragal.Venkatamuni@2004.hull.ac.uk), [d.n.davis@dcs.hull.ac.uk](mailto:d.n.davis@dcs.hull.ac.uk)}

## ABSTRACT

This paper investigates the concept of mind as a control system using the “Society of Agents” metaphor. “Society of Mind” is more than a collection of task-oriented and deliberative agents, it is a powerful concept for mind research and can benefit from the use of metacognition. The aim is to develop a self configurable computational model using the concept of metacognition. A six tiered control model or “Society of Mind” is designed and implemented that relies on a society of agents operating using metrics associated with the principles of artificial economics in animal cognition. This research investigates the concept of metacognition as a powerful catalyst for control and self-reflection.

Metacognition is used on BDI models with respect to planning, reasoning, decision making, self reflection, problem solving, learning and the general process of cognition to improve performance. Experiments are conducted with different combinations of agents.

One perspective on how to develop metacognition in a “Society of Mind” model is based on the differentiation between metacognitive strategies and metacomponents or metacognitive aids. Metacognitive strategies denote activities such as metacomprehension (remedial action) and metamangement (self management) and schema training (meaning full learning over cognitive structures). Metacomponents are aids for the representation of thoughts.

## KEY WORDS

Metacognition, Q-learning, metacomponents, norms. “Society of Mind” and simulation.

## 1. Introduction

Artificial Intelligence originated with the desire to develop artificial minds capable of performing or behaving like an animal or person. It has developed in a 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 behaviors 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. Intelligent behavior can be viewed as a combination of more simple behaviours. Imagine a simple reactive agent that can only move towards and collect a resource in the environment. Building an optimal or metacognition agent cannot be done with a single simple agent, as it needs to interact or take a help from other agents. Hence developing a cognitive architecture can be viewed from the perspective of Minsky [11], which leads to the development of many different types of simple agents, with different behaviours.

*“The Society of Mind is more than just collection of theorems. It is a powerful catalyst for Thinking about Thinking”* [14].

“Society of Mind” needs a catalyst like metacognition on top of the society of agents. Metacognition is a relatively new buzz word in cognitive theory. Metacognition is defined as thinking about thinking and can be viewed in two ways:

- (a) monitoring a group of agents in an intelligent or cognitive or robotic architecture (i.e. self reflection)
- (b) Making changes by adapting effective strategies in that group of agents.

Metacontrol is a part of metacognition. Metacognition agent is designed to testbed based on metacognitive strategies, such as Metacomprehension (remedial action), Self regulation (metamangement) and Schema training (meaningful learning).

The approach taken addresses these issues through the design and implementation of a model of mind building on the “Society of Agents” metaphor with different behaviors and capabilities encapsulated as micro-agents within an encompassing framework. For example the implemented architecture has reflexive (six behaviors), reactive (eight behaviors), deliberative (fifteen behaviors), perceptual (nineteen behaviors), learning (fifteen behaviors, fifteen agents), metacognition (thirty behaviors, one agent) and metacognitive (around hundred behaviors, single agent) agents. Indeed, from an extreme perspective in this distributed model of mind, there may exist many random combinations of reflexive, reactive, BDI (Belief, Desire, and Intention) agents or deliberative, perceptual, learner (Q learning), metacognition, and metacognitive agents.

Agent behaviors can be analyzed using many different metrics. The major metrics are metabolic activity, competition and social interaction with respect to environment and microeconomics. Application of economics on the artificial life to watch adaptive behaviours. This follows the microeconomic regularities such as cost and utility.

Testbeds and benchmarks are mainly using for simulating, comparing architectures and outcomes in the field of robotics or cognitive architectures. Pfeiffer [11] describes the fungus eater concept as a testbed for simulating models in emotion psychology. The fungus world environment allows the principles and behaviours of a robot or simulated animal or any artificial mind simulation to be monitored, measured and compared. This research explores metacognition mechanisms in developing optimal agents for the fungus world testbed.

## 2. Definition of Mind

Minsky [11] defines “*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.

## 3. Cognition

Animal cognition ([10], [16]) 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 behavior of human beings. Most cognitive scientists are interested in comparing human cognition with machine cognitions, few 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 [3], 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.

## 4. Laws on Animal Behaviours

The behavior of an animal has consequences which depend on situation [10]. 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 [16] the behavior 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 behavior is that an animal in any situation, apart from learning, responds by its inherited nature of its perception in its action and connection moves [3].

### 4.1 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 [10].

### 4.2 Cost and Utility Function

The decision making level in animals is defined in terms of cost functions and utility behaviours - the microeconomic level. Cost functions and utility behaviour in animals operate in such a way that a utility (for example, energy) is maximized or minimized [10].

### 4.3 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 ([10], [12]).

### 4.4 Optimal Behaviour

Animal behavior is a tradeoff between the native courses of action, i.e. physiological, and goal oriented behavior. An animal engaged with activities optimizes its pattern of behavior with respect to the use of energy and time. The animals engage activities in order to optimize its pattern of behavior 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 [10].

## 5. 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-comprehension) and communication (meta-communication). Metacognition is often simply defined as “thinking about thinking” ([1], [4] [5]). 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 [11] states that we cannot think about thinking, without thinking about thinking about something. Where that something is a behavior 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 monitoring a progress using cognitive tasks is termed metacognitive regulation ([1], [4], [5])

### 5.1 Metacomponents

Metacognitive aids or Metacomponents are used for the representation of thoughts [1] that can be made with the help of some aids such as. (1) Using an abstraction, metasyntactic variable (matching variables) or metacomponents and (2) goal setting variables such as Perceptual range, Affect, Norm, M-Norms and higher level rules are metacomponents.

The term “norm” is an interdisciplinary term, and can be used to refer to a standard principle or a model used for a right action. The executive processes that controls the other cognitive components are responsible for “figuring out how to do a particular task or set of tasks, and then making sure that the task or set of tasks are done correctly”.

## 6. Society of agents in Mind

There is a long history for the representation of the mind as a collection of agents. The artificial mind is a control structure for an autonomous software agent. A complete cognitive agent needs four separately and highly interrelated layers, which necessitates the consideration of ongoing arguments in agent research.

Any cognitive architecture contains a large collection of agents. Each agent may used in a different way to represent, and reason with, knowledge. Each agent is

specialized for some type of knowledge or cognitive process [11].

“Society of Mind” architecture to demonstrate how intelligent and optimal agent can be viewed as a large collection of agents or single agent as collective behaviors with well aligned rules (Follows Metacognition strategies) as a “Society of Mind [11].

Metacognition is useful for framing the constraints for this swarm intelligence. Swarm intelligence requires the inclusion of a mathematical theory of how the group of agents work together to achieve a common goal. Swarm intelligence uses different mathematical algorithms so as to cover all processing and functioning associated with the adopted architecture or mind model [2].

## 7. Design of Cognition and MetaCognition agents in “Society of Mind”.

The developing architecture can be viewed from one perspective of minsky [11]; this can be leads to develop a many different types of distributed simple agents, with different behaviors. These agents are distributed across different layers of architecture, so as to cover all processing and functioning associated with the adopted model of mind.

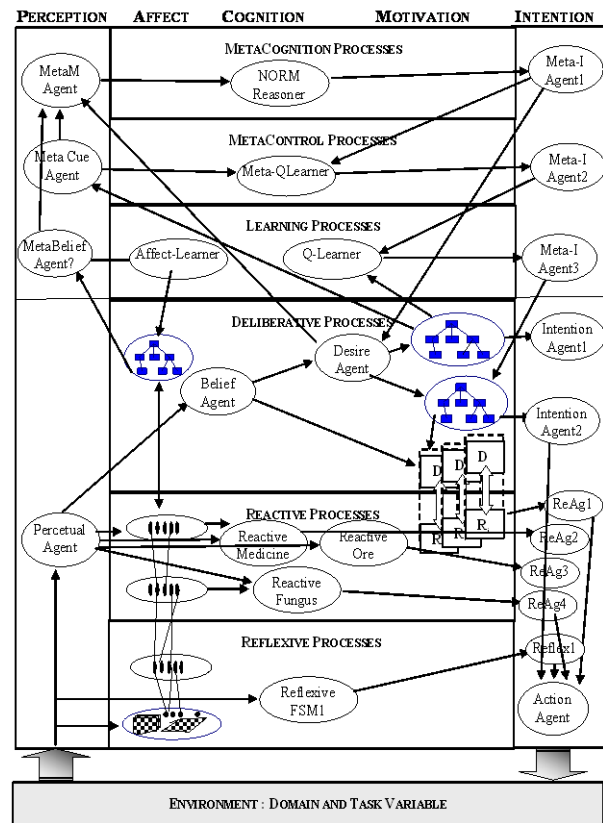


Fig 1. “Society of Mind” architecture

This society of mind architecture has designed and implemented for six layers which includes reflexive

reactive, deliberative (BDI Models), learning (Q-learner), metacontrol (BDI with Learning) and metacognition layers. This approach can be taken with further to develop different agent behaviours. Society of mind architecture consist reflexive (six behaviours), reactive (eight behaviours), deliberative (fifteen behaviours), perceptual (nineteen behaviours), learning (fifteen behaviours), metacontrol (thirty behaviours) and metacognition (around hundred behaviours) agents.

Indeed, from an extreme perspective distributed model of mind as control system, there may exist random, reflexive, reactive, BDI (Belief, Desire, and Intention) agent or deliberative, perceptual, learner (Q learning), metacontrol, and metacognitive agents.

## 8. Experimental Setup

Cognitive science theories are complicated and sometimes impossible to understand without simulating and observing in software. Testbeds and benchmarks are mainly using for simulating, comparing architectures and outcomes in the field of robotics or cognitive architectures. Pfeiffer [13] describes the fungus eater concept as a testbed for simulating models in emotion psychology. The fungus world environment allows the principles and behaviours of a robot or simulated animal or any artificial mind simulation to be monitored, measured and compared. This Fungus world testbed is implemented using SWI-Prolog. 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, crystal and medicine.

## 9. Different Agents in the Experiment

This experiment is concerned with the principles whereby an agent is competent for its resources, and so demonstrates intelligent behavior. Different types of agents (random, reflexive, reactive, learner, BDI-models, Metacontrol and Metacognition) 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.

### 9.1 Random

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

### 9.2 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 (FSM) 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.

## 9.3 Learner (Q-learning)

The reinforcement learning (RL) algorithm mainly started in the 1980s, in relation to the psychology of animals. This algorithm is the problem faced by the agent in the environment to learn through trial and error interactions. Reinforcement learning is learning, planning, and action selection paradigm based on maximizing reward [13].

### 9.3.1 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].

1. Initialize a table  $Q$  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

$$\text{New } Q(s, a) = \text{Old } Q(s, a) + (r(s) - r(s')) / r(s).$$

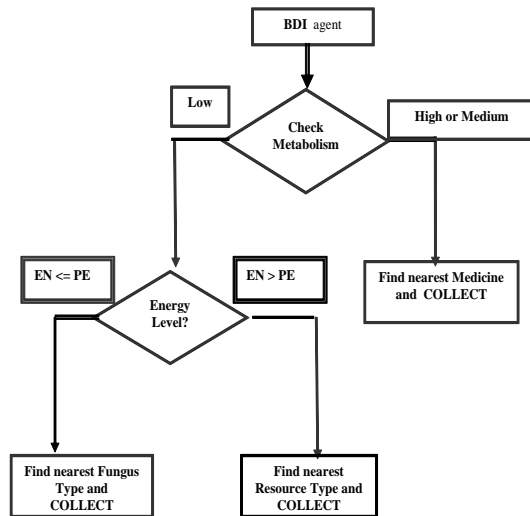
The  $Q$  values converged to their optimal values

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

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.

## 9.4 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, crystal, fungus or medicine) by making decisions towards achieve their goals. Mechanism in terms of BDI is given below



**Fig 2. Basic Belief-Desire-Intention Model.**

(1) Metabolism > Low,  
Searches for the nearest medicine to collect in order to lower the metabolism by through Reactive mechanisms.

(2) Energy Level <= Predicted Energy or smart energy level thinking or 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 > Predicted Energy or Decision variable  
Reactive Ore (Goal based behavior, move towards nearest resource) Uses FSM and Up|Left|Right|Down  
Find the nearest resource. Select the direction towards that Resource (Ore, Golden Ore or Crystal).  
Based on the Affect, Cost and utility function, the BDI1, BDI2, BDI3, BDI4 and BDI5 deliberative agents are framed.

## 9.5 Metacognition agent

Step1:-Map internal states onto Belief set from the perceptual range. The perceptual level increases the agent's belief set for sensing in the environment.

Example level 5 returns Sense List = [5-spacefree, 4-agent, 3-spacefree, 2-fungus, and 1-spacefree]

Update Belief Set with perceptions and perceptual range.

Step2:-Use Affect mechanism to find a need of the metabolism and need of a food.

Step3:- Use metacomponents such as Norms or M-Norms (Such as Norm1, Norm2, Norm3, ETC are standard rules) to decide which BDI model to choose in write time by using write decision (optimal decision)by comparing resources available and balance the resources in a testbed.  
Example Norm 1:

Collected ore is Ore1 + Golden\_ore1,  
Collected ore > 0,  
Norm\_oreBDI = Perceived ore / Collected ore.  
Perceived ore = No\_Ore + NO\_Gold,  
Norm\_oreBDI = Perceived ore / Collected ore.  
Collected crystal is Crystal1.

Step4:- (metacomprension or remedial action) Select appropriate Belief-Desire-Intention combination (BDI-Ore, BDI-Crystal, BDI-Ore Crystal, ETC), by comparing the architectural results.

Step5:- (Metamanagement) Uses M-Norms to switch the BDI Models (Such as BDI-Ore, BDI-Crystal, BDI- Ore Crystal, ETC),

Step6:- (Schema training) Use Q-Learning for Optimal steps taken from agent by using M-Norms and Affect Mechanism (Metacognition level).

Step7:- Repeats the steps (Step1 to Step6) until Simulation ends.

Norm is a standard principle or a model used for the right action. Multi norms, figuring out how to collect resources to optimize their patterns of behavior with respect to the use of energy and time, and then making sure that the task or set of tasks are done correctly.

## 10. Simulation Results

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

### 10.1 Simulation 1

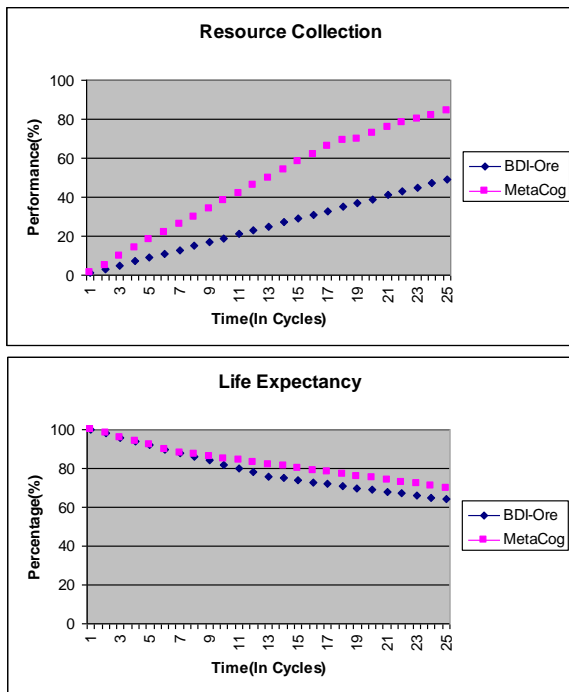
The collection of standard ore, golden ore and crystal (resources) by agents Random, Reflexive, Learner, and BDI-model agents are as follows: Random agents collects 16% of resource, Reflexive agents collects 26% of resource, Learner agents collects 45% of resource and BDI-model agent collects 50% of resource.

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 64% of energy.

### 10.2 Simulation 2

The experimental results in between the BDI (better among simulation 1) and Metacognition agents are given below.The collection of standard ore, golden ore and crystal by BDI-model and Metacognition agents are as follows. BDI-model agent collects 50% resource and

Metacognition agent collects 82% of resource. BDI agents are left 64% energy and Metacognition agents are left 71% of energy.



Graph 1. BDI v/s Metacognition

## 11. Conclusion

The result concludes that Metacognition agents are better than other cognition and Simple BDI agents. A Metacognition agent collects more resource and manages the higher life expectancy than all other agents.

This result proves a concept of metacognition is a powerful catalyst for control and self-reflection. Metacognition used on BDI models with respect to planning, reasoning, decision making, self reflection, problem solving, learning and the general process of cognition improved the performance

The implementation of MetaCognition concept on a Society of agents to demonstrate a Mind, provides a solutions or at least some steps or progress towards a Minsky's theoretical issues of "Society of Mind" and Minsky's A, B and C-Brian. This research paper explained how to build an artificial model that combines reflexive, reactive, deliberative, learning, metacontrol and metacognition processes across the "Society of Mind" architecture to demonstrate how intelligent and optimal agent can be viewed as a large collection of agents or single agent as collective behaviours as a "Society of Mind". Finally, this research gives a clear roadmap for researches, to develop a Metacognition concept on different applications.

## References

- [1] J. Adkins Metacognition, university of Saskatchewan, Canada.
- [2] M.A. Bedau Artificial life: Organization, Adaptation, and Complexity from the Bottom, 512, 2003, [Online] Available at [www.sciencedirect.com](http://www.sciencedirect.com).
- [3] J. Berger's 'why look at animals' Pittsburgh: Carnegie Mellon university. Available at Report 1998, CMU-CS-91-204,
- [4] M.T Cox, Metacognition, problem solving and aging, Cognitive Science Tech. Rep. Atlanta, Georgia Institute of Technology, 1994, College of Computing No. 15.
- [5] M.T. Cox, *Metacognition in Computation: A selected research review*, *Artificial Intelligence*. 169(2), 2005, 104-141.
- [6] D. N. Davis, *Architectures for Cognition and Affect* (Ed. *Visions of Mind*: Idea Group, Hershey, PA, Information Science Publishing, 2004).
- [7] Flavell J H, 1979, *Metacognition and cognitive monitoring: A new area of cognitive developmental inquiry*. *American Psychologist*, 34, 906-911
- [8] S. Franklin, *Artificial minds*, (A Bradford book, MIT press, 1995).
- [9] S. Hanks, M Pollack and P.R.Cohen., Benchmarks, 1993, *Test-beds, Controlled*
- [10] D. McFarland, T. Bossler, *Intelligent behavior in animals and robots* (MIT press, Massachusetts, , 1993)
- [11] M. Minsky, *The society of Mind*, (Cofounder of the artificial intelligence, Laboratory, MIT, 1985).
- [12] Nason S and Laird J E, *Soar\_RL integrating reinforcement learning with Soar*, 2004. Available at <http://www.sciencedirect.com/science>
- [13] R. Pfeifer, 1993, the new age of the Fungus Eater. *Second European Conference on Artificial Life, ECAL 93, University Libre de Bruxelles*, 1993.
- [14] P. Singh, *Examining the Society of Mind*, *Computing and Informatics*, 1001, 1023 v, 2003, MIT Media lab.
- [15] P. Singh, M. Minsky, I Eslick, *Architecture for computing Commonsense*. *BT Technology Journal*, 22(4):, 2004, 201-210
- [16] E.L.Thorndike, *Animal intelligence: Experimental studies*. New York: Macmillan, 1911.
- [17] E.N.Zalta, *Stanford Encyclopedia of Philosophy* [online], available: [www.platostanford.edu](http://www.platostanford.edu), [Accessed at 5 May 2005].