“Society of Mind” Cognitive Architecture

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Abstract

This paper describes the design and development of six tiered Society of Mind Cognitive Architecture (SMCA). SMCA model designed that relies on mind as a control system, and uses “Society of Agents” metaphor.” Society of Agents” describes collective behaviours of simple and intelligent agents. “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. This research uses the concept of metacognition as a powerful catalyst for control, unify and self-reflection in a cognitive architecture. SMCA model has designed and implemented for six layers which includes reflexive, reactive, deliberative (BDI), learning (Q-learner), metacontrol and metacognition layers. Important issues in developing Society of Mind Cognitive Architectures include task effectiveness, goal achievement, and the ability to perform well in novel situations.

1. Introduction

Cognitive architecture refers to the design and organization of mind, and provides the means for the integration of cognitive abilities [15]. Young [28] defines a cognitive architecture as an embodiment of the scientific hypothesis of human and nonhuman cognition. Different types of cognitive architectures can be designed, implemented and applied to various tasks. Cognitive architectures are designed to be capable of performing certain behaviours and functions based on our understanding of human and nonhuman minds.

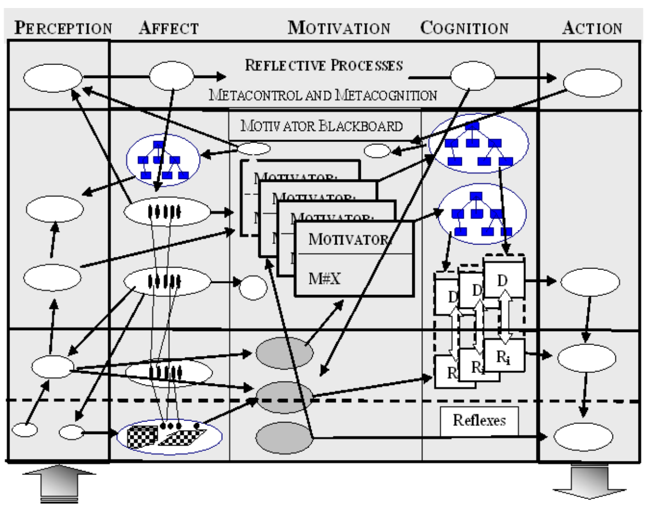
The evaluation of cognitive architectures has always been challenging. Several common concepts and different methodologies have been applied on developing new architectures. There are many examples of developed cognitive architectures developed for different purpose by using different concepts available in different disciplines. For example general overview of cognitive architecture [21] ACT-R [2], SOAR [22], CRIBB [4], EM-ONE [24], CogAff [25] and CAMAL [9] [11], etc.

Different cognitive architectures and paradigms can be said to be modelling different aspects of cognition, different aims, with different metaphors, and from different contexts. To develop a better and sophisticated cognitive architecture, researchers need to understand: (1) the sufficient description of theoretical, design and implementation level of different architectures and; (2) the missing, common and generalised factors of relevant cognitive architectures. The newly developing Society of Mind Cognitive Architecture (SMCA) extends the Davis [9] [11] basic CAMAL cognitive architecture with extra processing layers and uses society of mind and metacognition concepts.

2. CAMAL

CAMAL (Computational Architectures for Motivation, Affect & Learning) architecture was proposed by Davis [9] [11] from the University of Hull. CAMAL is a theoretical framework developed from Guardian, Cogaff’s [9] [11] [25] three column, three level architecture; and Sense-Think-ACT-Cycles mechanism, CRIBB [27], and Singh’s EM-ONE [24] commonsense-frame based architectures. The purpose of CAMAL is used to simulate artificial minds.

CAMAL cognitive architecture attempting to demonstrate some theoretical; and design issues associated with, linking perception and action through motivation and affect mechanism. CAMAL uses different testbeds and physical environments for demonstration. Presently using testbeds are five-aside football; tile-worlds; fungus world; and physical environments like Robot-CAMAL for control of multiple reactive architectures. Some of the experiments are still under investigations [11]. As Figure 1 depicts CAMAL has four tiers and five columns architecture. This provides a basic template for all explanations [11]. Cognition tasks involve the control of external and internal behaviour of the environment. The control of behaviour, for further of its goals. Affect mechanism in CAMAL uses BDI models for adaptive decision making across the architecture. BDI (Beliefs, Desires Intentions) are the mental components present in rational agent architectures [5]. CAMAL [9] uses a logical model of reasoning based on Beliefs, Desires, and Intentions that mirrors the motivation and learning. The BDI model intentions are adopted plans or strategies for achieving desires. The adoption of specific plans converts desires into achieved intended desires. Lewis research on Affect-CRIBB distinguished affect as emotion in terms of their magnitude and type. Emotion is a kind of Affect. The emotions are anger, joy, intelligence, etc. A-CRIBB theory affect mechanism uses control states and motivators and affordances [11].



“Figure 1. Basic CAMAL Architecture.”

CRIBB [27] model uses BDI models for representing reasoning capabilities of five year old child. This model has been extended with an affordance affect to map onto motivational structure. The CAMAL agent navigates around the environment, recognizes the actors or objects. This follows some of the cognitive capabilities like, perception, problem solving and reasoning. Action means recognizing the object and navigating around the environment. CAMAL architecture has explored to adopt affect and learning models over the affect model. This affect magnitude is useful for “fitness function”. The investigation of deeper learning capabilities should, in general, bring beneficial results. The CAMAL principles are under investigation, through satellite project; and a metacontrol and metacognition mechanism on extended CAMAL with extra processing layers, for distributed model of mind [11] [26].

3. Comparison of cognitive architectures

Cognitive architectures can be assessed in terms of their ability and efficiency to support the construction of models and simulations of cognition tasks. The comparison Table 1 given below explains the different types of cognitive models, their purposes, and skills used to develop a cognitive architecture. ACT-R [2] and SOAR are well known and very old cognitive architectures. ACT-R and SOAR are very popular and contains many users. Popularity is due to their flexibility for researchers to expand for different useful applications. ACT-R and SOAR [22] incorporate aspects of human-like reasoning and specific problem-solving capabilities. ACT-R is an example of a moderately specified architecture, in which one can build such simulation models. There are some features that are important in the study of complex tasks that ACT-R is not well-adapted to model. ACT-R has certain errors in chunks management, and time delay in execution. According Wahl and Spada [27], the CRIBB can be re-implemented by using general architecture of ACT- R, and is useful. Some of the theoretical constructs adopted for CRIBB’s inference schema is directly correspondence with ACT-R. The operational resources of a child can be expressed with source activation (production rules) in ACT-R.

“Table1. Cognitive model’s Comparison Table”

Cognitive model	Refrence	Mechanism	Purpose
ACT-R	Anderson(1976)	Production systems	To demonstrate and understand human Skills
SOAR	Newell(1980)	Chunking mechanisms	learning, reasoning, decision making. (Human level)
EM-ONE	Singh(2005)	Encoded in the form of Frames (6 layers)	Commonsense thinking and Reflective reasoning.
CRIBB	Wahl and Spada (2000)	Belief, Desire, Intentions(BDI)(By using Primary and Secondary representations)	Reasons like a 5 year old child
CogAff	Sloman (2001- Ongoing)	Reactive, Deliberative Reasoning and Meta-management	Generic purpose (Human, animals &machine minds)
CAMAL	Davis (2002 - Ongoing)	Belief, Desire, Intentions(BDI) Models for reasoning	Artificial minds

Singh [24] argues that SOAR [22] addresses orthogonal systems, because SOAR is a rule based system. EM-ONE is built by using rules. Singh [24], claims that it is not a difficult to implement version of EM-ONE using SOAR as a substrate. In, SOAR “architecture” refers to the minimum set of mechanisms. In EM-ONE, architecture refers to the “structure and arrangement of commonsense knowledge and processes”. This discussion, reviewed some important different researchers views on cognitive architectures aims, representations, principles, working mechanisms, common factors, generalized factors, missing factors, limitations, problems, advantages and disadvantages.

4. Metacognition

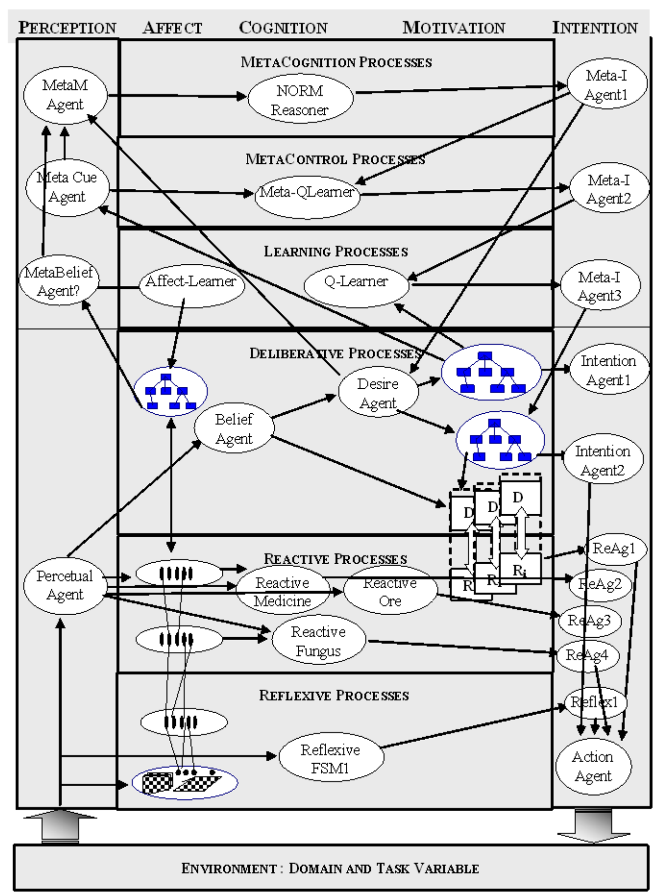
The study of metacognition has grown since the 1970s. In educational psychology, Flavel [12] and others developed a model of children's cognition about a memory (metamemory), understanding (meta-comphrension) and communication (meta-communication). Metacognition is often simply defined as "thinking about thinking" [1], [7], [8]. 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 [18] 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 (the self reflective) monitoring of progress using cognitive tasks is termed metacognitive regulation [1], [7], [8].

5. Design of SMCA

Artificial mind can be viewed as a control structure for an autonomous software agent. Any cognitive or computational architecture can be viewed as either a single agent or a large collection of agents. There is a long history of representing mind as collection of agents, dating back to Selfridges's Pandemonium model [23]. This model attempts to explain mind as a collection of agent type tiny demons. The pioneers such as Selfridge [23], McCarthy [16], Allen Newell and Herbert Simon [20], Minsky [18], Fodor [14], Baars [3], Brustoloni [6], Anderson [2], Franklin [13], Sloman [25], Davis [9] [11] and Singh [24] were viewed computational theories of mind, from artificial agents.

The developing architecture can be viewed from one perspective of minsky [18]; this can be leads to develop a many different types of distributed simple agents, with different behaviours. These agents are distributed across different layers of architecture, so as to cover all processing and functioning associated with the adopted model of mind.

This society of mind architecture has designed and implemented for six layers which includes reflexive layer, reactive layer, deliberative layer (Includes BDI models), learning layer (Q-learner), metacontrol and metacognition layers. This approach can be taken with further to develop a different agent behaviours like, example approximately, presently working agents has, reflexive(six behaviours), reactive(eight behaviours), deliberative(fifteen behaviours), perceptual(nineteen) ,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) agents or deliberative, perceptual, learner (Q learning), metacontrol, and metacognitive agents. The designs of individual agents are discussed in the next sections.



"**Figure 2. Society of Mind architecture**"

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, crystal and medicine. Different types of agents (random, reflexive, reactive, learner and BDI-models, metacontrol and metacognition) are introduced in this experiment.

5.1 Reflexive Level

Reflexive agent's fits for the first layer of the SMCA (Society of Mind approach to a distributed Cognitive Architecture) shown in Figure 2. Reflexive agents are designed to perform reflexive behaviours. Agents will make decisions and take actions based on the given environmental rules. Reflexive agents are simple, reactive, and instinctual. Reflexive actions are controlled from a finite state machine. Generally, reflex action is basically derived from human and animal biological neuromuscular action. The reflexes are built-in mechanisms that can operate quickly before thinking. There are two ways that reflexes can behave: (a) simple reflex, which is automatic and requires no learning experience and (b) combined reflexes. A finite state machine behaves like a simple mathematical animal, that can be regarded as a discrete-time system with finite input and output sets. This responds to only a finite number of different stimuli (the input set or alphabet) and output alphabets. Algorithm shows mapping of finite state machine (FSM) from perceptual inputs. The example FSM works as follows:

(1) Input * State → New state;
(2) Input * State → Output.

Finite state machines output is mapped onto the agent action. FSM rules make use of the external and internal state conditions. Finite state machine rules can be framed for each piece of resource. The current work make use of four reflexive behaviours (refer Algorithm1): (1) first rule (Rx1) uses finite state machine, and moves arbitrary; (2) second rule (Rx2) uses finite state machine, and moves randomly;(3) third rule (Rx3) uses FSM, and move towards centre of the environment; and (4) fourth rule (Rx4) uses finite state machine, and moves towards edges of the environment.

The reflexive actions or goals satisfy as those specified by the deliberative agents. The design for the fungus testbed includes four different reflexive agents. A BDI agent in deliberative layer determines which of the reflexive control mechanisms are active according to the goals the entire architecture attempts to satisfy. These goals determines the number of different types of reflexive behaviours required for this specific testbed (reflexive-BDI model is described in the next section). Reflexive agents understand the environment sensors, such as the locations of each edge or centre point, etc. For each move, they check the corresponding adjacent positions and determine the proper direction, either up, down, left or right. The tasks of such agents are to navigate environment and avoid collisions with other agents in the environment.

Algoritm1. Reflexive agent design algorithm

Rx1: Uses FSM and up|left|right|Down (1^{st} condition):-
Prefers move > nothing,
Prefers up | left| right | down (arbitrary).
Rx2: Uses FSM and up|left|right|down (2nd condition):-
Prefers move > nothing,
Prefers Random direction.
Rx3: Uses FSM X up|left|right|down (3rd condition):-
Prefers move nothing,
Prefers move towards centre of the environment.
Rx4: Uses FSM X up|left|right|down (4th condition):-
Prefers move nothing,
Prefers move towards edge of the environment.

5.2 Reactive level

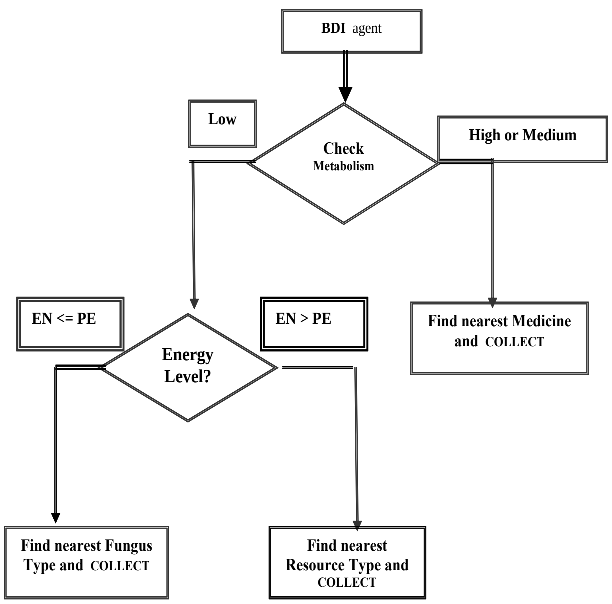
Reactive agents compromise the second layer of the distributed cognitive architecture shown in Figure 2. Reactive agents are designed to perform goal oriented behaviour, building on the mechanism of the reflexive agents described in the previous section. The goals they attempt to satisfy as those specified by the deliberative BDI agents (described in the next section). The design for the fungus testbed includes seven different reactive agents. The deliberative BDI determines which of the reactive control mechanisms are active according to the goals (refer Algorithm 2). The entire architecture attempts to satisfy. These goals are either task related or agent-internal resource related, and determine the number of different types of reactive agent required for this specific testbed.

Algorithm2. Resource Reactive algorithm

Goal based behaviour towards resource
Goal: one of (ore, golden ore and crystal)
Find the nearest resource by their distance,
Select the direction towards nearest resource,
Move towards resource direction (Left| Right | Up | Down). If No Resource within Perceptual Range follows reflexive actions (i.e. Move towards edges of the environment).

5.3 Deliberative Level

Deliberative agents compromise the third layer of the distributed cognitive architecture shown in Figure 2. The design of deliberation mechanisms for the fungus testbed includes five different types of BDI agents. The BDI determines which of the reactive or reflexive control mechanisms are active according to the goals of the entire architecture attempts to satisfy. These goals are either task related or agent-internal resource related, and determine the number of different types of reflexive and reactive agent required for this specific testbed. For example, As in Figure 3 depicts BDI-Ore (BDI1) selects and controls the combination of reactive-fungus, reactive-ore, reactive-golden-ore and reactive-medicine behaviours. BDI5 or BDI-Reflexive agent selects and controls the combination set of reactive-fungus, reactive-medicine and reflexive behaviours.



“Figure 3. Belief-Desire-Intention Model.”

BDI (Belief- Desire-Intention) model has different group of coordinated capabilities to meet a particular intention. BDI models follow the reactive mechanisms. Agents exhibit decision making capabilities near a decision variable boundary. The energy spent (maximum cycles follows low metabolism) in each move of BDI types exhibits minimal or minimized (due to maintenance of low metabolism), and utility is also maximized. BDI agents engaged with activities optimize its pattern of behavior with respect to energy and time. For example, if the energy level is lesser than threshold or predicted energy, then switch into the fungus consumption. If the energy level is sufficient or more than threshold or predicted energy, then it switch towards goal oriented (i.e. collection of ore).This mechanism demonstrates physiological and goal oriented behaviour.

BDI agent follows the reactive actions in each move based on given rules and decision variables (refer Figure 3). Some BDI models favor specific goals towards: (1) ore; (2) crystal; (3) medicine, or (4) fungus. BDI models work in terms of a fixed threshold and adaptable energy use.

The different versions of deliberative models uses in this experiment are: BDI-Ore (BDI1), BDI-Crystal (BDI2), BDI-ore-and-crystal (BDI3), BDI-adaptive (BDI4); and BDI-Reflexive (BDI5). Deliberative agents in a fungus world testbed are capable of performing different tasks.

5.4 Learning Level

The fourth layer of the architecture is the learning processes layer. Learning changes decision making at one level about actions at another level for tasks defined at yet a further level. This layer is in effect controlled through connections to the metacontrol level. Reinforcement learning is learning, planning, and action selection paradigm based on maximizing reward [19].Update the state: $s' \rightarrow s$. Q-learning algorithms work by estimating the values of state-action pairs. The value Q(s,a) (refer Algorithm3) 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.

Algorithem3. Q-Learning Algorithm

Let $\mathbf{Q}(s, a)$ be the expected discount of reinforcement of taking action a in state s, then continue by choosing actions optimally [13] [26].

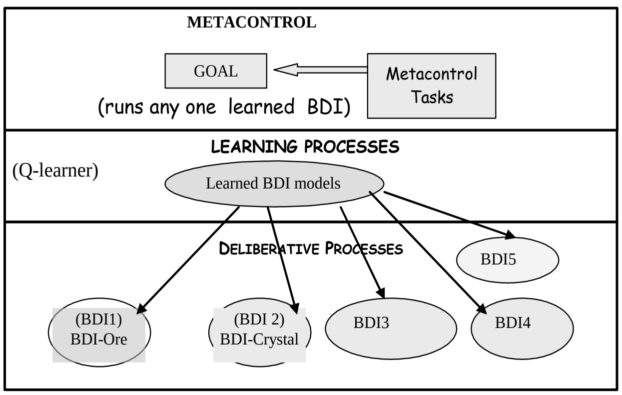
1. Initialize a table **f** with states **S**, actions **A** and the **Q** (utility or reward) value estimates.
2. Select an action a (where $a \in \mathbf{A}$) and execute it.
3. Observe the immediate reward r. Reward is defined using some agent relation, for example distance to desired object. Observe the new state s’, achieved by action a on state s, where $a \in \mathbf{A}$ and $s \in \mathbf{S}$.
4. Update the table entry for **Q** value using an appropriate rule, for example

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

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

5.5 Metacontrol level

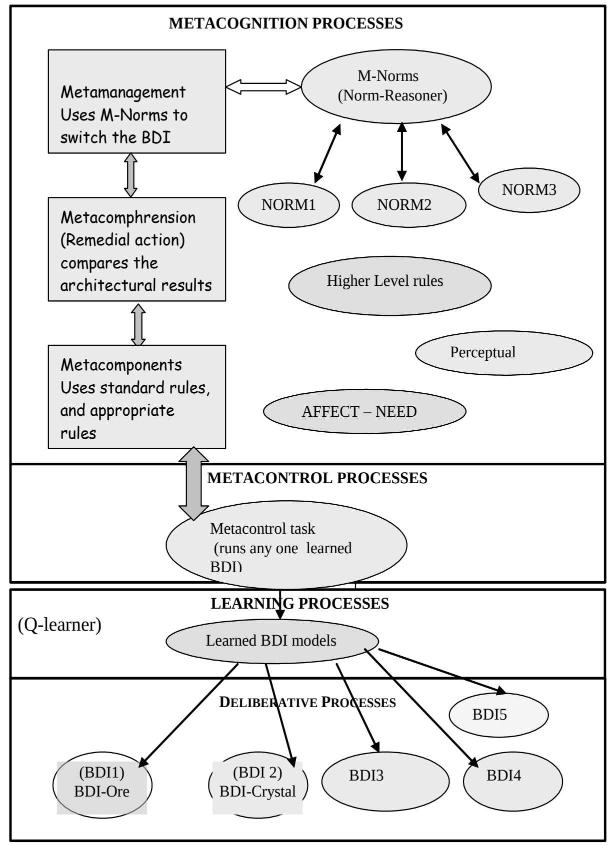
Metacontrol agent decides which deliberative agents are to be learned and ready to perform in different conditions. The deliberative actions are called control actions. A Meta controller determines the relevant control actions.Metacontrol agent’s compromises the fifth layer of SMCA as shown in Figure 2. The metacontrol agent learns actions upon the environment. The agent calculates all the combinations of deliberative agent’s states (inputs) and actions. Metacontrol agents have different levels of skills, such as reflexive, reactive, deliberative, or learning capabilities. As Figure 4 depicts metacontrol agent can select and controls any of one of the decision models such as :(1) learned-BDI-ore, (2) learn-BDI-crystal, (3) learned-BDI-ore and crystal, (4) learned-BDI-adaptive and (5) learned-BDI-reflexives. BDI agents should learn themselves by trained method. So adding learning methodology makes more effective. Reward is a goal of the metacontrol agent. The metacontrol task level agent does follows :(1) when and what to learn; (2)what decision model to select and (3)when to change between architecture possibilities. Metacontrol agents can select the BDI model. But cannot reason for higher level thoughts. Due to this reason metacontrol agent can not reason and change the BDI models.



“ Figure 4. Metacontrol Task ”

5.6 Metacognition Level

This is the final layer of SMCA mind model. This layer uses norms to control the architecture. Metacontrol agents can choose BDI models, but cannot change the deliberative models with reasoning (Figure 5). The metacognition level agent works by comparing the architectural level, and uses (1) learned-BDI-ore, (2) learn-BDI-crystal, (3) learned-BDI-ore-crystal, (4) learned-adaptive and (5) learned-BDI-reflexive. The metacognition agents can change the framework of BDI agents with reasoning. This level works to control and monitor the deliberative models. The deliberative models can be switched off or on based on the norms. The different combination of agents is organized for different goals or different tasks: (1) collection of ore (2) collection of ore golden ore; and (3) collection of crystals can be performed by society of agents. K-lines can cause cascade effects within an SMCA. These K-lines turn agents on and are interconnected to each other. For example, the reactive-ore, BDI-ore and BDI-ore-crystal combination of agents can collect ore. Reactive-crystal, BDI-crystal and BDI-ore-crystal combination of agents can collect crystals. This illustrates that the SMCA follows Minsky’s K-line theorem.



“Figure 5. Metacognition agent design ”

Metacognition concept on BDI agents selects the most appropriate type BDI agents (BDI-ore, BDI-crystal, BDI-ore-crystal, etc). Metacomponents in Metacognition layer helps for switching BDI agents on and off state. The actors for each move compares, reviews and change their goals from their self reflection processes. The self-reflection process, updated from the norms. Norms adjusted the thoughts by giving feedback. The norms decide based on environmental and agent situations. The actors can change and control their behaviours as BDI-ore, BDI-crystal and BDI-ore-crystal, if necessary in the environment.

“Algorithm 4. Metacognition”

Step1:-Map Internals states onto Belief Set from the perceptual range or perceptual level increases the agent’s belief set for sensing in an environment. Example level 5 returns Sense List = [5-spacefree, 4-agent, 3-spacefree, 2-fungus, and 1-spacefree].Updates Belief Set with Perceptions and perceptual range.

Step2: -Use Affect mechanism (metacomponent), to find a need of the Metabolism and need of a food.

Step3:- Use a 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.

Step4:- (Metacomphrension or Remedial action) Select Appropriate Belief-Desire-Intention Combination (BDI-Ore, BDI-Crystal, BDI-Ore Crystal, ETC), by comparing the architectural results.

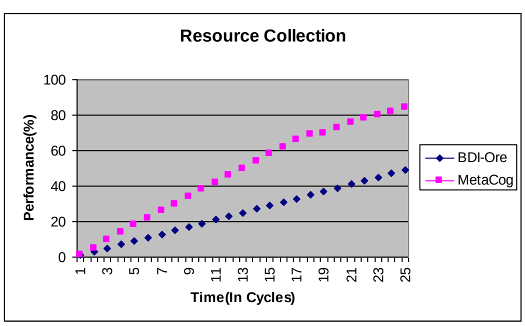
Step5:- (Metamanagement) Uses M-Norms to Switch the BDI Models (Such as BDI-Ore, BDI-Crystal, BDI- Ore Crystal, ETC),

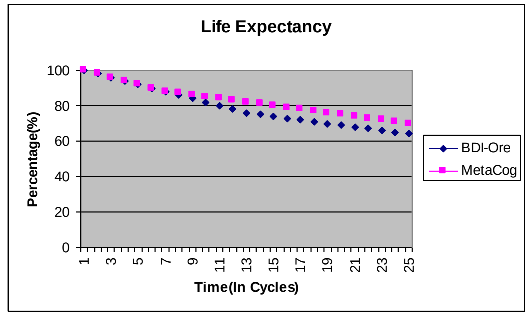
Step6:- (Schema training) Use a Q-Learning (given below) for Optimal steps taken from agent by using M-Norms and Affect Mechanism (mtacognition level).

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

6. 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 in different level of architecture were employed for these experiments. The higher level agent performs better than lower level agents in SMCA. For instance comparing third level agent with sixth level agent as follows: (Graph1 depicts BDI-model and mtacognition agents' performance) as follows: BDI-model agent collects 50% resource and metacognition agent collects 82% 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 BDI agents are left 64% energy and metacognition agents are left 71% of energy.





Graph 1. Performance of agents

7. Conclusion

This research paper illustrated Society of Mind approach to a Cognitive Architecture. The mind is a control system, and uses the "Society of Agents" metaphor. Simulation demonstrated Minsky's approach of "Society of Mind." Society of Mind Cognitive Architecture is the first architecture, completely viewing cognitive architecture in the perspective of "Society of Mind" and society of agents.

The result concludes that BDI with 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, unification 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.

This research paper explained how to build an cognitive architecture 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 and metacognition concepts on cognitive modeling.

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