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Metacognition using classifier system: A step approaching intelligent agents

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Abstract-- ***Meta-cognition*** **allows one to monitor and adaptively control cognitive processes. It guides people to select, evaluate, revise, and abandon cognitive tasks, goals, and strategies. Also, meta-cognition can play an important role in human-like software agents. It includes meta-cognitive knowledge, meta cognitive monitoring, and meta cognitive regulation. The main purpose of this research paper is to understand the principles of natural minds and adopt these principles to simulate artificial minds. We consider the conscious software agent, "CMattie" which has its cognitive science side (cognitive modelling) as well as its computer science side (intelligent software). We describe the incorporation of meta cognition in CMattie using fuzzy classifier system including Genetic algorithm and Probabilistic approaches.**

Keywords**—** Meta cognition, **Cognitive functionality, classifier system, SDM, Fuzzy Perception**

I. Introduction

As soon as a child is born it is given the daunting task of creating a reality. It must form the knowledge and goal structures that will dictate how it interacts with the world around it – and why. From relatively few initial clues each child must learn everything that it needs to survive and prosper. Some of this learning is just a matter of noting the common sensory results to actions performed under a given situation, simple muscle control, for example. Almost all learning beyond these first simple steps, however, requires that the child be able to judge not only what an action does, but also whether that result is a desirable one or not. Luckily for humanity, evolution has provided us with a set of innate sensory inputs that are pre-wired in our brains to give us pleasure, pain, happiness, sadness or any number of other feelings. To take steps in accomplishing this in an artificial system, a sufficiently general mechanism called metacognitive mechanism is being used in CMatie, a software agent, and extended to more closely approximate some human cognitive phenomena. [1]

Cognitive architectures are designed to be capable of performing certain behaviors and functions based on our understanding of human and non human minds. In this respect, Artificial Intelligence has the desire to develop artificial minds capable of performing or behaving like an animal or person and making great strides in a number of directions like artificial intelligent systems, having reasoning and emotions.

II. Principles of Minds.

Human behaviour is a trade offf between the native courses of action, i.e. physiological and goal orientedbehavior.. Human is engaged with activities 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 learn decision boundaries. The mechanisms of designing a machine are different from the animals' kingdom, but the principles remain the same.

Goal directed Behavior in artificial minds:

As shown in Fig. 1, goal directed behavior in artificial minds (a human, animal or machine) involves representation of the goal to be achieved. This means that behaviour can be actively controlled by internally represented states. Goal directed behavior aims to minimize the difference between the "desired" state of affairs and the actual state of affairs. This difference is called as error in the behavior. This can be corrected by using different factors. The design of an animal is genetically based and product of natural selection. But the robot is based on human engineering principles. However, the principles of their function and goal achievement can be similar.

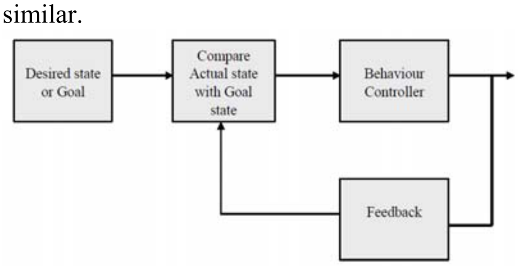


Fig.1 Goal directed Behaviour

III. Principles of Brain

We need to understand the functionality of natural brain prior to its implementation in intelligent software agents. Among the most recent and exciting developments in neuroscience has been the introduction of methods for imaging the function of the intact human brain. This in turn has opened up the opportunity to study the involvement of the brain in uniquely human activities, such as reasoning and complex forms of decision making.

However, only recently has it become possible to track the activity of specific brain areas in normal human subjects while they perform cognitive tasks. This has been made possible by the advent of methods such as positron emission tomography (PET scanning) and functional magnetic resonance imaging (fMRI). Most current studies use fMRI, because it has the advantage of being noninvasive (requiring no injections), can exploit the large installed base of MRI scanners, and provides the best available combination of information about the location and timing of brain activity. Neuroimaging studies have driven substantial progress in understanding the neural mechanisms underlying emotional and cognitive processes.

The Human Cerebrum-
Higher order thinking and decision making:

To understand how the brain learns, a basic understanding of the anatomy and physiology of the brain is necessary. The largest portion of the brain is called the cerebrum. The cerebrum is the most highly evolved part of the brain, and is sometimes called the neocortex. Higher order thinking and decision making occurs here. The cerebrum is composed of two hemispheres that are connected by a neural highway, the corpus callosum. Information travels along the corpus callosum to each hemisphere so that the whole brain is involved in most activities. Each cerebrum is composed of four lobes: frontal, parietal, temporal, and occipital (Fig.2). Each lobe is responsible for specific activities, and each lobe depends on communication from the other lobes, as well as from the lower centers of the brain, to complete its jobs.

At the coarsest level(Fig.3), the brain can be divided into the neocortex—the folded sheet of cells that forms the outer surface of the brain—and deeper, evolutionarily older sub cortical structures (below the cortex) that include the striatum (near the brain's core) and the brainstem (at its base). It has long been known that several sub cortical structures, particularly those in the brainstem that release the neurotransmitter, dopamine, and those in the striatum that are influenced by the release of dopamine, respond directly to rewarding events themselves or to their anticipation. These structures are believed to be involved in fundamental forms of reinforcement learning. These, and other sub cortical structures responsive to valenced events (i.e., events associated with positive or negative utility), make direct connections with several structures within the frontal lobes (the part of the brain just behind the forehead) and temporal lobes (the part of the brain just beneath the temples). [2]

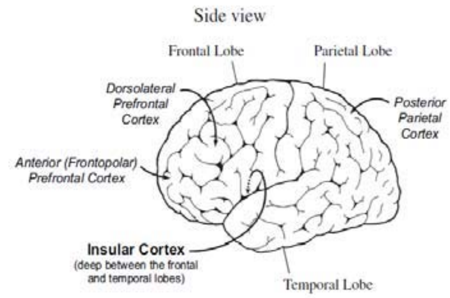


Fig 2 the Human Cerebrum: Side View

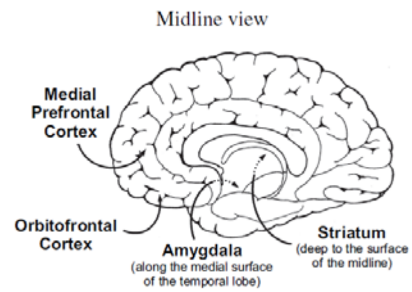


Fig 3 the Human Cerebrum: Midline View

These cortical areas include medial and orbital regions of frontal cortex (along the inner surfaces and base of the frontal lobes, respectively), the amygdala (along the inner surface of the temporal lobes), and insular cortex (at the junction of the frontal and temporal lobes) as shown in Fig. 3. These cortical structures, along with their sub cortical counterparts, are classically referred to as the limbic system of the brain, and are thought to be critical to emotional processing. The prefrontal cortex occupies one-third of the neocortex and is one of the brain areas that has expanded most in humans, relative to other primate species. The prefrontal cortex also partially encompasses some of the emotion-related areas noted above.

At the broadest level, two categories of function can be ascribed to prefrontal cortex: reasoning abilities and the capacity for cognitive control—that is, the ability to guide thought and action in association with abstract goals or intentions, especially when this requires overcoming countervailing habits or reflexes (Miller and Cohen, 2001). By exploiting this type of knowledge about brain organization and function, and determining which brain systems are associated with a particular behavior, researchers may be able to understand better the processes driving the cognitive behavior.

IV. METACOGNITION

Meta-cognition allows one to monitor and adaptively control cognitive processes. Its importance in human thinking, learning, and problem solving is well established. Humans use meta cognitive monitoring and control to choose goals, assess their own progress, and, if necessary, adopt new strategies for achieving those goals, or even abandon a goal entirely. Meta cognition, or the ability to think about one's own thinking, evolves as the brain matures. Meta cognition includes models of thinking, automation of conscious thought, accessing automatic processes, practice effects, and self-awareness. It also includes being aware of one's own thoughts, feelings, and actions, and their effects on others. [3]

However, there has also been growing interest in trying to create, intelligent agents which are themselves meta cognitive. It is thought that agents that monitor themselves, and pro actively respond to problems, can perform well, for longer, with less need for human intervention. It can be hypothesized that meta cognitive awareness may be one of the keys to developing truly intelligent artificial systems.

Elements of Meta cognition :

From one perspective, there are four elements to meta cognition :

- Meta memory : Meta memory refers to learner awareness of which strategies are used, and should be used, for certain tasks. It is used for storing the information about a cognitive task.
- Meta comprehension: It is used for detecting and rectifying the errors. This helps to improve the performance.
- Self-regulation: Self-regulation refers to meta cognitive adjustments agents make concerning errors.
- Schema Training: Schema training is a meaningful learning for generating own cognitive structures or frameworks.

V. ACTION SELECTION & COGNITIVE FUNCTIONALITY

An autonomous agent is a system situated in, and part of, an environment, which senses that environment, and acts on it, over time, in pursuit of its own agenda. Biological examples of autonomous agents include humans and other animals. Non-biological examples include some mobile robots, and various computational agents, including artificial life agents, software agents and many computer viruses [4]. In biological agents, the agenda arises from evolved drives and their associated goals; in artificial agents, the agenda arises from drives and goals built in by their designers. Every autonomous agent is structurally coupled to its environment. We'll be concerned with animals, including humans, thought of as autonomous agents, situated in their environments, sensing their environments and acting on their environments (Fig.5). Every autonomous agent, including humans and other animals, spends it waking life in the moment-to-moment responding to the only question there is: "What shall I do next?" Thus, this deciding what to do next constitutes the major activity of any agent between each sensing of its environment and the agent's next action upon it. Using this, one shall refer to this process of choosing what to do next base on sensing the current environment and current goals as cognition.

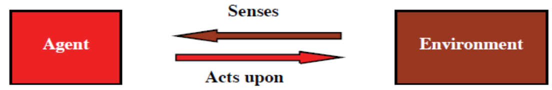


Fig.5 Every autonomous agent continually and, cyclically, Senses its environment and acts upon it in pursuit of its goals.

This cognitive behavior of agents can be modeled in the following figure.

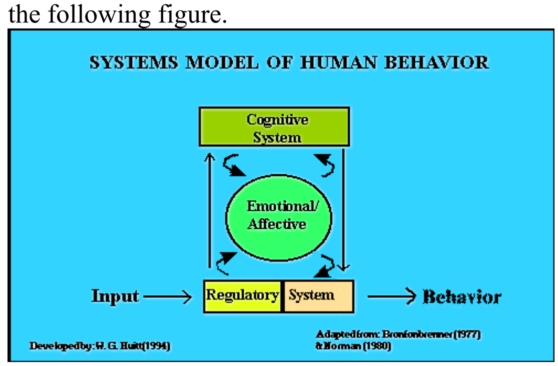


Fig.6 Systems Model of Human Behaviour

Here we'll be concerned with *"conscious" software agents only.* These agents are cognitive agents in that they consist of modules for perception, action selection (including constraint satisfaction and deliberation), several working memories, associative memory, episodic memory, emotion, several kinds of learning, and metacognition. They model much of human cognition. But, in addition, these agents include a module that models human consciousness according to global workspace theory (Baars 1988, 1997). Our aim in this work is twofold. We want to produce a useful conceptual and computational model of meta cognition and consciousness. At the same time we aim to produce more flexible, more human-like software agents [5] having metacognition.

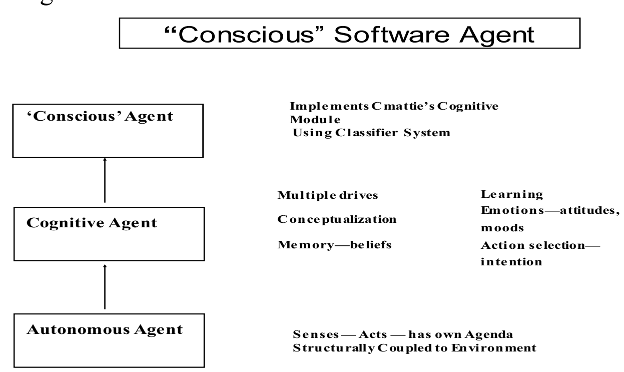


Fig.7: Conscious, Cognitive & Autonomous Agent

Implementing meta cognition in software agents can be very exciting and challenging. If we want to build more human-like software agents, we need to build meta cognition into them. By doing this, we provide agents a meta-system that allows them to overcome internal disorders, to choose an efficient strategy, and to self-regulate. CMattie's name derives from the fact that she implements the global workspace theory of consciousness (Baars 1988 1997), along with some other cognitive theories concerning meta cognition, episodic memory, emotion, learning, etc. Baar's global workspace theory is a cognitive model of the human conscious experience. CMattie is expected to be more intelligent, more flexible and more adaptive. Several functional modules are being added to improve her performance [6]. CMattie's architecture and mechanisms make her "think" and act more like humans do. This paper focuses on incorporation of metacognition into CMattie.

The mechanism can also learn which intermediate states or goals should be achieved or avoided based on its primitive drives. In addition, a psychological theory of consciousness is modeled that allows the system to come up with creative action sequences to achieve goals even under situations of incomplete knowledge. The result is an architecture for robust action selection that learns not only how to achieve primitive drives, but also learns appropriate sub-goals that are in service of those drives. It does this in a way that is cognitively plausible and provides clear benefits to the performance of the system. [1]

VI. Metacognition in CMattie

CMattie is a "conscious" clerical software agent. She composes and emails out weekly seminar announcements, having communicated by email with seminar organizers and announcement recipients in natural language. She maintains her mailing list, reminds organizers who are late with their information, and warns of space and time conflicts. There is no human involvement other than these email messages. CMattie's cognitive modules include perception, learning, action selection, associative memory, "consciousness," emotion and metacognition. Her emotions influence her action selection [5].

CMattie's brain consists of two parts, the A-brain and the B-brain [11]. The A-brain performs all cognitive activities. Its environment is the outside world, a dynamic, but limited, real world environment. The B-brain, sitting on top of the A-brain, monitors and regulates the A-brain. The B-brain performs all metacognitive activities, and its environment is the A-brain, that is, the A-brain's activities. Fig. 8 depicts an overview of CMattie's architecture. In this paper, we will discuss only the mechanism of the B-brain and the interaction between some relevant modules in the A-brain and the B-brain. We describe a study of the design of metacognition using a fuzzy classifier system. This system allows the B-brain to satisfy one of the meta-drives of the B-brain, "Stopping any endless loop in which the A-brain finds itself." The endless loop here means that the A-brain repeats itself in an oscillatory fashion. In particular, the B-brain monitors the understanding process of the A-brain, and acts when any oscillation problem occurs. The classifier system allows the B-brain to monitor, to act, and to learn a correct action to stop an endless loop in the A-brain.

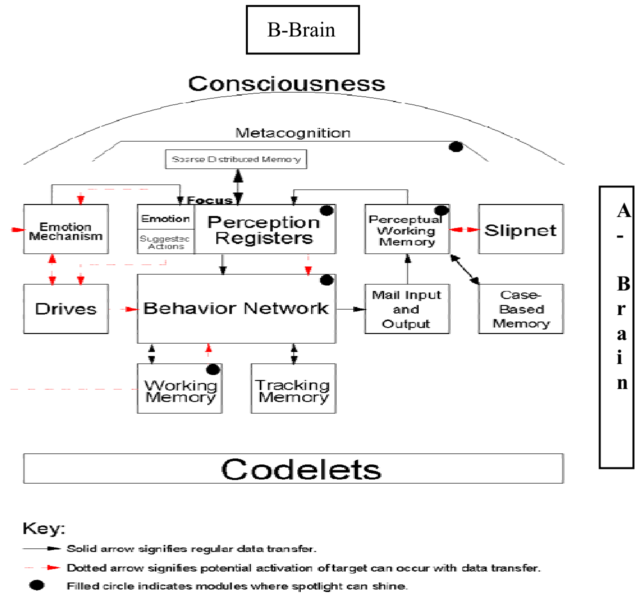


Fig. 8 Overview of CMattie's Architecture

SDM (Sparse Distributed Memory) is a content addressable, associative memory technique which relies on close memory items tending to be clustered together, with some abstraction and blurring of details. We use the auto-associative version of SDM as an associative memory in the conscious software agent, CMattie. SDM retrieves the behaviors and emotions associated with an incoming percept. This association relies on similar percepts having occurred in the past and having been associated with some behaviors and emotions. So, observing some percept later on should trigger into attention the previous behaviors taken and emotions aroused when similar percepts were observed in the past. Each perception register contains some seminar key value like seminar organizer, speaker, date, location, etc… The results obtained so far are good and promising. Some other possible use for Sparse Distributed Memory in CMattie is the disambiguation of each perception register by removal of some inherent noise or misspells.

A. Oscillatory thinking problem of A-brain:

Metecognition directs CMattie to a higher degree of understanding in that she can handle oscillation problems during her understanding phase.

Oscillatory behavior might occur as the perceptual mechanism goes back and forth between two message types unable to decide on either. Meta cognition might then send additional activation to one message type node in the slipnet, effectively forcing a decision, even a wrong one. The metacognition module can also affect CMattie's behavior by tuning global parameters, for example in the behavior net [7].

At present, CMattie's natural language understanding occurs in two stages [12]. First, the incoming message is classified as one of the nine message types. This job is done with the help of the slipnet), an associative memory (see Fig.9 and Fig.10). The nine message types are: Initiate a seminar, Speaker topic, Cancel a seminar session, Conclude a seminar, Change of time, Change of place, Change of topic, Add to mailing list, and Remove from mailing list. For a given incoming message, the nine message-type nodes in the slipnet will have different activation levels. The one with the highest activation level is selected as the proposed message type, a "winner takes all" strategy. But all the other message-type nodes retain their activations and are candidates for the next selection, if the current winner proves to be wrong. The appropriate template is then chosen based on the message type, and placed in the perceptual workspace (see Fig. 8). Each message type corresponds to one template. Different message types have different slots in their templates. Fig. 9 shows the Speaker-Topic Message template. Codelets (processors) then begin to fill the slots (e.g. speaker name, title of the talk, time of the seminar, date, place, email address of sender, etc.) in the template. If any mandatory slots (e.g. speaker name) are finally not filled, the chosen template, and therefore the proposed message type, is not correct. So the message type with the next highest activation level is chosen as the new proposed message type, the corresponding template is chosen, and its slots are filled. The process repeats until there is a proposed message type with all the mandatory template slots filled. This proposed message type is correct and so is the information in the template [8].

The A-brain performs all the above activities. The B-brain takes over when the A-brain trying to understand an irrelevant message realizes that she does not have enough knowledge to do the job. It detects the situation and does something to prevent her from repeatedly looking for a message type. A classifier system can act as the action selection mechanism for the B-brain. In this particular case, the B-brain monitors whether there is an oscillatory thinking (endless loop) during the A-brain's understanding process, and learns how much activation to send to the nine message-type nodes in the slipnet so that the endless loop is stopped. Fig. 10 depicts how the B-brain interacts with the A-brain during the understanding process.

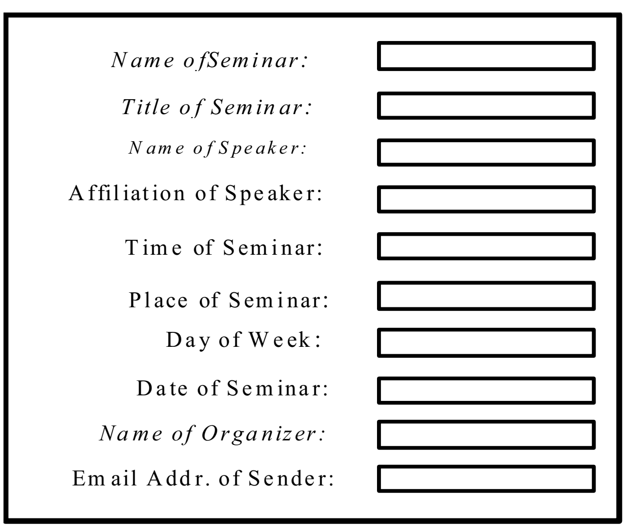
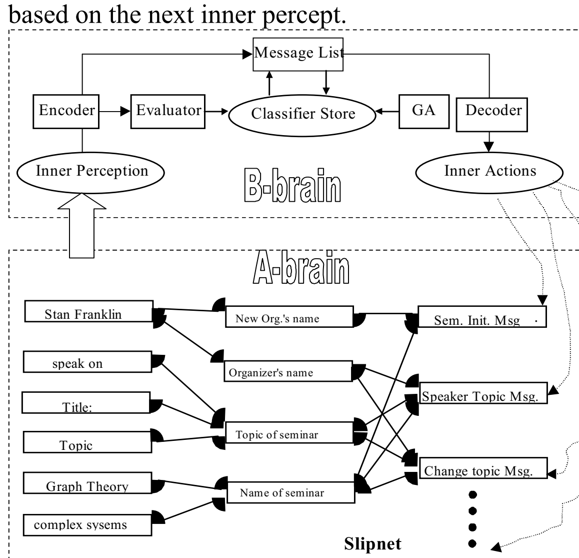


Fig. 9: Speaker-topic Message Template
(Italic shows mandatory slots)

B. Mechanism of the B-Brain

CMattie's meta cognition module i.e. the B-brain, is quite complex, being comprised of several distinct sub-modules. An inner perception sub-module monitors the A-brain. It consists of sensors and decoders. Decoders differ from sensors in that they perform inferences. Sensors get the raw data from the A-brain and decoders put them into internal representations. The fuzzy classifier system at the heart of metacognition's action selection needs fuzzy inputs. The fuzzifier sub-module contains membership functions that interpret a real (crisp) number to express the fuzzy value and uses them to fuzzify each inner percept. Thus each numeric value of an inner percept is replaced by the corresponding linguistic value. These fuzzy percepts are then fed to the encoder sub-module, which encodes them into finite length strings and puts them in a message list. These fuzzy string percepts may match antecedents of classifiers. This matching activates collection of classifiers from the fuzzy rule base sub-module of classifiers, often referred to as the classifier store. This fuzzy rule base of classifiers contains the metacognition modules' knowledge of what to do in a given situation. Metacognition then uses classifiers from the fuzzy rule-base to infer appropriate fuzzy string actions that are posted in the message list by winning classifiers. The decoder sub-module decodes the string action to a set of fuzzy actions. Using the membership functions, the defuzzifier sub-module transforms these fuzzy values into crisp numeric values that can be used by the inner actions sub-module. The appropriate actions are then taken. Hence after an inner percept is encoded as a string percept, it is put in the Message List. This string percept is actually the environment message (or the current state of the A-brain sensed by the B-brain). So perception can be conceptualized as sensation plus inference

Metacognition in CMattie is implemented as a classifier system in order that it may learn. Learning actions always requires feedback on the results of prior actions. The evaluator sub-module is implemented by a reinforcement learning algorithm that assigns reward or punishments to classifiers based on the next inner percept.



(Fig. 10: Interaction between the A-brain and the B-brain during the Understanding Process)

C. The Classifier System

The classifier store contains a population of classifiers. Each classifier consists of a condition, an action and strength, such as 0100: 001011011110100110, 3.3333. The condition part is a template capable of matching internal string percepts, 0000, 0001, 0010, 0011, 0100, 0101, 0110, 0111, 1000, and 1001. The action part consists of sending activation to each message-type node in the A-brain. There are four fuzzy levels of activation: low (00), medium low (01), medium high (10), and high (11).

In the beginning, the B-brain has no idea about which rule is good, or which rule is bad. After it takes some actions on the A-brain, and gets feedback (The Evaluator changes the strength of a fired classifier), it will have a better idea. The B-brain gradually learns good rules, in other words, a correct action taken on the A-brain in some situations.

At each time step only one classifier acts on the A-brain. Only this classifier is evaluated and its strength updated. All the other unfired classifiers keep their current strengths. Once a classifier's condition is matched to the current inner percept, that classifier becomes a candidate to post its action to the Message List. It is not possible to let all matched classifiers post their actions there. The probability of a matched classifier posting its action in the message list is proportional to its strength. The action on the message list that acts on the A-brain is selected at random.

A classifier with a high strength does not mean its action is correct. It only means this action is close to the right action. When a correct action is performed, the classifier system will stop since the loop is stopped. On the other hand, some classifiers have high strength because they make the loop smaller. However, we should not give them advantage over others because they cannot stop the loop. If we choose the one with the highest strength every time, some classifiers with better actions may not have a chance to be fired, and a chance to be evaluated. In the classifier system, only when a classifier is fired and its action is performed, it is evaluated. Randomly selecting an action from the message list gives every active classifier a chance to perform its action and to be evaluated. If no classifiers' condition matches a percept, then some classifiers with lower strengths are selected, and their condition parts changed to match the current percept.

A selected string action is decoded by the Decoder. 00 is decoded as low, 01 medium low, 10 medium high, and 11 high. Later, the Inner Actions Module sends activation to the message-type nodes in the A-brain. The actual activation levels are 0.5 (low), 1.5 (medium low), 2.5 (medium high) and 3.5 (high). The Evaluator decides whether the action provided by a fired classifier is good or bad.

The Evaluator is implemented by a reinforcement learning algorithm[13]. It assigns reward or punishment to classifiers based on the next inner percept sensed from the A-brain. Notice that the B-brain has no teacher. In order to see how good or how bad its current action is, it has to see what the next percept is. If after an action is taken, the loop in the A-brain becomes smaller than before, this action gets some reward. If the loop in the A-brain is stopped, this action is a correct action and the classifier system stops.

A sense-select-act cycle is a cycle during which the B-brain senses from the A-brain, selects an action (provided by a fired classifier), and performs the action on the A-brain. However, if the B-brain cannot stop a loop in the A-brain in twenty sense-select-act cycles, the Genetic Algorithm Module is activated to evolve new, possibly better classifiers. Classifier's strength is used as a fitness measure.

Genetic algorithms are search algorithms based on natural evolution. In this system, the selection is proportional to each classifier's strength. Only two classifiers with the same condition can participate in a crossover. This allows searching for new actions for a given percept (condition part). Suppose for a given situation in the A-brain, no current classifier has a correct action, crossover may generate a new and correct action to deal with such a situation. The crossover position (point) for each pair of classifiers is randomly generated. The strength of the offspring is the average of its parents' strengths.

In addition to crossover and mutation, new classifiers using probability vectors is produced [14]. A probability vector is used to maintain statistics about the correct action string. One probability vector serves all the classifiers with a given condition. There are eighteen numbers in each probability vector for eighteen bits in the action part of the classifier. For example, the probability vector for condition 0100 may start as: <0.5, 0.5, 0.5, 0.5, ………0.5>. This means that, in the beginning, the B-brain has no idea about the correct action string. It could be 0 or 1 in each bit position with the same probability. After a classifier 0100 : 011000101100111010 is fired and an action 011000101100111010 acts on the A-brain, suppose the Evaluator gives a middle reward to this action. The probability vector will be updated to close to 011000101100111010 since this action got a reward. It could be updated as <0.25, 0.75,0.75, 0.25, … >. This means the first bit of the correct action string would be more like 0, and second bit 1, etc. Later, if a classifier 0100 : 111001101110111010 is fired and gets a punishment, the probability vector will be updated in the opposite direction. The formula used to update a probability vector is as follows: (Let LR represents the learning rate and i the position in a vector or a string)

Pvector[i] = Pvector[i]*(1-LR) + WinnerVector[i]*LR, when the winner gets a reward.

Pvector[i] = Pvector[i]*(1-LR) - WinnerVector[i]*LR, when the winner gets a punishment.

In this way, the B-brain takes every opportunity to learn the probability vector, and keeps a record of such learning. The B-brain updates its probability vector whenever an action is taken. Thus the new classifiers produced by using probability vectors are more likely to be correct.

In most GA-based applications, every individual in the population is evaluated at every time step (or generation). In a classifier system, only one individual is chosen and evaluated. So the B-brain must take every opportunity to learn from the feedback of each action. The probability vectors are very helpful in keeping track of what a right action should be. They help the B-brain to learn quickly.

VII. Conclusions and Future Work

The "conscious" software agent architecture offers a promising vehicle for producing autonomous software agents that are life-like in their interactions with humans via email. They will be life-like in that they understand the human correspondent's natural language and are able to respond, also in natural language. The architecture and mechanisms underlying these abilities are themselves, life-like in that they are modeled after human cognition and consciousness. Such "conscious" software agents show promise of being able to duplicate the tasks of many different human information agents.

CMattie, had an impoverished metacognition module that prevented oscillations in her processing and tuned the parameters of her behavior net to make her more or less goal oriented or more or less opportunistic, etc. Metacognition in CMattie was implemented as a separate B-brain with its own decidedly different mechanism that looked down on what the rest of CMattie was doing (Minsky, 1985) and interfered as needed. Here a classifier system is discussed to implement metacognition in the B-brain in order to solve the oscillatory thinking problem in the A-brain which can give more potentiality to the construction of an intelligent software agent.

Experimentation with CMattie is just beginning. Evaluation of her performance promises to be straightforward. In future a Genetic algorithm and Probabilistic classifier system can be devised to make the metacognitive module more efficient in handling problems of oscillation.

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