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THE USE OF EMOTIONS IN THE IMPLEMENTATION OF VARIOUS TYPES OF LEARNING IN A COGNITIVE AGENT

DISSERTATION

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I dedicate this research to my beloved Sioui Maldonado Bouchard and Dr.Jean-Yves Housset

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ABSTRACT

Professional human tutors are capable of taking into account past and present events, and are driven by social concerns. To be considered a valuable technology for improving human learning, a cognitive tutoring agent must be capable of the same. Given that dynamic environments evolve, a cognitive agent must evolve to accommodate structural modifications and the arrival of new phenomena. Consequently, the ideal cognitive agent should possess learning capabilities whose mechanisms are based on the types of learning found in human beings; i.e., emotional learning, episodic learning, procedural learning, causal learning, and learning of regularities (Purves et al., 2008, Squire and Kandel, 1998).

Reconstructing and implementing human learning capabilities in an artificial agent is far from being possible with our actual knowledge and computers capacities. To achieve human-like learning and adaptation in machines, or to simply better understand human adaptability, we have to design human-inspired learning mechanisms. The strategies for the implementation of learning mechanisms in agents have been to use one type of learning or a collection of learning types in one single mechanism (Vernon et al., 2007). However, the various types of learning are functionally incompatible (Sherry and Schacter, 1987). This work describes the conception of learning and of the emotional version of CTS (CELTS); that is, a complex cognitive agent equipped with emotions and a number of learning mechanisms such as emotional, episodic and causal learning. CELTS' performance is upgraded by the parallel, complementary and distributed functioning of learning mechanisms and emotions.

Keywords: cognitive agent, emotions, episodic learning, causal learning.

RÉSUMÉ

Les tuteurs professionnels humains sont capables de prendre en considération des événements du passé et du présent et ont une capacité d'adaptation en fonction d'événements sociaux. Afin d'être considéré comme une technologie valable pour l'amélioration de l'apprentissage humain, un agent cognitif artificiel devrait pouvoir faire de même. Puisque les environnements dynamiques sont en constante évolution, un agent cognitif doit pareillement évoluer et s'adapter aux modifications structurales et aux phénomènes nouveaux. Par conséquent, l'agent cognitif idéal devrait posséder des capacités d'apprentissage similaires à celles que l'on retrouve chez l'être humain; l'apprentissage émotif, l'apprentissage épisodique, l'apprentissage procédural, et l'apprentissage causal.

Cette thèse contribue à l'amélioration des architectures d'agents cognitifs. Elle propose 1) une méthode d'intégration des émotions inspirée du fonctionnement du cerveau; et 2) un ensemble de méthodes d'apprentissage (épisodique, causale etc.) qui tiennent compte de la dimension émotionnelle. Le modèle proposé que nous avons appelé CELTS (Conscious Emotional Learning Tutoring System) est une extension d'un agent cognitif conscient dans le rôle d'un tutoriel intelligent. Il comporte un module de gestion des émotions qui permet d'attribuer des valences émotionnelles positives ou négatives à chaque événement perçu par l'agent. Deux voies de traitement sont prévues: 1) une voie courte qui permet au système de répondre immédiatement à certains événements sans un traitement approfondis, et 2) une voie longue qui intervient lors de tout événement qui exige la volition. Dans cette perspective, la dimension émotionnelle est considérée dans les processus cognitifs de l'agent pour la prise de décision et l'apprentissage.

L'apprentissage épisodique dans CELTS est basé sur la théorie du Multiple Trace Memory consolidation qui postule que lorsque l'on perçoit un événement, l'hippocampe fait une première interprétation et un premier apprentissage. Ensuite, l'information acquise est distribuée aux différents cortex. Selon cette théorie, la reconsolidation de la mémoire dépend toujours de l'hippocampe. Pour simuler de tel processus, nous avons utilisé des techniques de fouille de données qui permettent la recherche de motifs séquentiels fréquents dans les données générées durant chaque cycle cognitif.

L'apprentissage causal dans CELTS se produit à l'aide de la mémoire épisodique. Il permet de trouver les causes et les effets possibles entre différents événements. Il est mise en œuvre grâce à des algorithmes de recherche de règles d'associations. Les associations établies sont utilisées pour piloter les interventions tutorielles de CELTS et, par le biais des réponses de l'apprenant, pour évaluer les règles causales découvertes.

Mots clefs: agents cognitifs, émotions, apprentissage épisodique, apprentissage causal.

CHAPTER I

INTRODUCTION

Although there is no consensus on the definition of the term *agent*, learning[1] (Langley, 1996) is definitely one of its important properties (Wooldridge, 1999, Franklin and Graesser, 1997). The term *agent* spawned a wide area of discussion between scientists ranging from bacteria-like tropistic agents (such as Braitenberg's vehicles (1984)), to clever but inflexible cambrian-intelligent agents (Brooks, 1999). In the last three decades, scientists have tried to design cognitive agents that can interact agilely with humans. The success or failure of the designed and implemented agent architectures is, at least, in part owed to the learning mechanisms that are implemented by the designers (Russell and Norvig, 2003, Franklin and Graesser, 1997, Franklin et al., 2007, Subagdja et al., 2008). Humans are endowed with various types of learning mechanisms, for instance emotional learning, episodic learning, procedural learning, etc (Purves et al., 2008, Squire and Kandel, 2000). It has been suggested recently that all types of learning in humans are directly influenced by emotions (Damasio, 1994, Damasio, 2003, Bower, 1992). Until recently, the strategies for the implementation of learning mechanisms in agents were to use only one type of learning[2] for everything or to use a loosely

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[1] Learning is "*the improvement of performance in some environment through the acquisition of knowledge resulting from some experience in that environment*" (Langley, 1996).
[2] For instance, the Soar architecture can only learn new production rules (Vernon et al., 2007).

connected collection of learning types in one single mechanism[3] (Vernon et al., 2007). However, various types of learning are functionally incompatible (Sherry and Schacter, 1987).

The goal of this study is to integrate emotions and a number of learning mechanisms which work in a parallel, complementary and distributed manner into one single cognitive agent. We introduce the Conscious-Emotional Learning Tutoring System (CELTS), a new version of CTS (Dubois, 2007). CELTS is a cognitive agent based on the Baars' workspace theory of consciousness (Baars, 1997). According to Baars' theory, the human mind is made up of a vast number of dumb, domain-specific, specialists designed to solve problems quickly, presumably by applying fast and frugal heuristics (Gigerenzer, 1991, Gigerenzer and Todd, 2000). When a specialist, or a group of specialists, works out its solution to a part of a problem, it broadcasts the found solution to all other specialists, who can in turn apply their expertise to the problem. Through this broadcasting, a global workspace emerges, which we experience as consciousness. Damasio (2000) postulated that sensation, emotion, cognition and thought are important processes that play crucial roles in consciousness and are in perpetual and repetitive interaction among themselves. Accordingly, cognitive agents must at least be equipped with perception, memory, learning, emotions, motivators, reasoning and actions (Newell, 1990, Alvarez 2006, Faghihi et al., 2008a).

Working with CELTS has allowed us to conceive learning differently than what was done before. First, emotional learning can now be conceived as a pre-theoretic imprecise term that covers two distinct mechanisms: 1) short route: a quick but dumb (i.e., reflex-like) mechanism that prepares us to quickly pull away from or confidently approach a situation; 2) long route: the modifications in workspace processing brought about by the variation in the valence assigned to all events as a result to the dumb specialist's processing.

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[3] Learning in the ACT-R architecture occurs in symbolic and sub-symbolic levels under an integrated learning mechanism (Vernon et al., 2007).

Second, one important form of memory is episodic memory. Episodic memory is the memory of what, where and when. It allows people to travel back mentally through time as well as imagine the future. Recently, studies have demonstrated the role of the hippocampus and its influences on episodic memory consolidation in the human brain.

Third, causal learning is the process through which we come to infer and memorize the cause for an event based on previous beliefs and current experiences that either confirm or invalidate previous beliefs (Maldonado et al., 2007). Causal learning is an important factor in reasoning, for it is considered crucial to many characteristics of cognition such as selection, abstraction, planning, etc.

Finally, emotion influences different types of memory and learning in human such as causal learning (Bower, 1992, Squire and Kandel, 2000, Cándido et al., 2006).

To explain how we integrated emotions and different types of learning into CELTS, we organized this document in the following manner:

Chapter two goes over several cognitive science and neuroscience principles regarding various types of memory, emotion[4], emotional learning, episodic learning, and causal learning in humans. We then turn to neuroscientific and computational neuroscientific models to discuss the role of various neurological structures in the formation of emotions and episodic memories. We present a current computational neuroscientific model of the interaction between the hippocampus and the cortex in the formation of episodic memories, in which the hippocampus functions as a temporary store recording, in a one-shot learning fashion, every experience an individual has and serves in the cortical consolidation of frequent events. We then present a current computational neuroscientific model that postulates the creation of

[4] Emotions are divided into three components (Purves et al., 2008): behavioral action such as motor output, conscious experience such as fear, and physiological expression such as one's heart rate raise when facing to a danger.

new hypotheses in inductive reasoning, for which activation in the left prefrontal cortex (LPFC) is very important. In chapter three, we start by describing a range of agent and cognitive architectures. We also describe CTS, from which CELTS was created (Dubois, 2007). It is a cognitive architecture based on IDA (Franklin, 2003), The architecture of CTS was based on neurobiological and neuropsychological theories of human brain function. CTS was designed to provide assistance during training in virtual learning environments. It was integrated in an intelligent tutoring system called CanadarmTutor which provides assistance to astronauts learning how to manipulate Canadarm2, the robotic telemanipulator attached to the International Space Station (ISS). CanadarmTutor (Nkambou et al., 2006) includes a virtual simulator of the ISS and Canadarm2, which allows user to execute multiple procedural tasks by manipulating the robotic arm. CTS observes the astronauts' arm manipulations and provides assistance as a tutoring decision-maker. In particular, the virtual simulator sends all manipulation data to CTS, which, in turn, sends advice to learners so they can improve their performance. Usually, learning tasks consist in moving the arm from one configuration to another. This is a complex task, as the arm has seven joints and the astronaut has a limited view of the arm; three monitors are connected to approximately 15 cameras installed on the ISS. Hence, the astronauts must constantly choose the best three cameras (out of 12) to view the environment, and adjust their parameters accordingly.

At the end of section three, we make a brief comparison between the most often implemented learning mechanisms in cognitive agents and CTS.

In chapter four, we explain how emotions and emotional learning are integrated to CELTS. The general logic of our approach is stated. We base our approach on various computational neuroscientific and psychological models of emotions. These posit two distinct neurological routes from perception to emotions, the so-called "short route" and "long route". These two routes present distinct learning mechanisms, reaction times and phenomenological profiles- the short route being fast and unconscious and the long route being slower and involving consciousness. At the end of this chapter, we present the results from our testing of CELT's emotional learning and reactions.

In chapter five, we begin by a brief review of the existing work concerning episodic learning in cognitive agents. We then explain our proposition to equip CELTS with an episodic memory and learning by combining elements of the Emotional Mechanism (EM) and episodic memory. At the end of this chapter, we present the results from our testing of CELT's episodic learning and the collaboration of its emotional mechanism and episodic learning. In chapter six, we begin by a brief review of the existing work concerning Causal Learning in cognitive agents. We then propose our new architecture combining elements of the Emotional Mechanism (EM) and Causal Learning. At the end of this chapter, we present the results our testing of the collaboration of emotion, episodic learning and causal learning in CELTS.

In chapter seven, we present the conclusion; the limits of the implemented mechanisms, our plan for the future and the contribution of this study to the computer science and cognitive science are addressed.

CHAPTER II

MEMORIES, REASONING, EMOTIONS

Memory and emotions are two inseparable and crucial parts of human cognition (Huitt, 2003, Atkinson and Shiffrin, 1968 , Dolan, 2002). Emotions influence cognitive processes and vice-versa (Damasio, 1999, Rolls, 2000, Dolan, 2002). Neuroscientifc evidence has demonstrated the influence of emotions in different types of memories, especially when individuals learn new information (Squire and Kandel, 2000, Phelps, 2006, Damasio, 1994). Accordingly, we start by explaining the neuroscientific and computational neuroscientific models of emotions and emotional learning. We then explain the neuroscientific and computational neuroscientific models of memories. We focus particularly on those of episodic memory and episodic learning. We then briefly explain the various types of reasoning, and finally, we discuss the causal approach to reasoning.

2.1 EMOTION

Emotion is an unclear concept that is not easily definable (Thompson and Madigan, 2007, Alvarado et al., 2002). Various definitions and very important responsibilities were given to emotion. However, there is no consensus for one definition. Charles Darwin (1872) defined emotion as a survival and adaptable capacity of living organisms. He described emotions as innate, universal and communicative entities. From the behavioural point of view, emotions are supposed to organize our behaviour- an independent entity which influences the individual decision making, attention and learning. From a sociocultural point of view, we may interpret feelings[5], which are part of emotions, as being individuals' response to internal stimuli such as the feeling of pain due to a headache, or the feeling of sadness at a loved one's death. Thus, emotions in part from our relationships and help us to interact with others. Accordingly, emotions exist in the personal and social dimensions of an individual. In fact, emotions allow us to adapt and accept new changes in our dynamic environment.

The six basic emotions described by Paul Ekman are surprise, fear, disgust, anger, happiness, and sadness. They are particular and specific to each individual (Picard, 2003) and influence humans' cognition directly (Squire and Kandel, 2000, Phelps, 2006).

Recent studies in neurobiology showed that the source of emotions are a mix of several biochemical, sociocultural and neurological factors (Westen, 1999). Purves (2008) divided emotions into three following processes : 1) a behavioural action (such as agitation, escape, and aggression); 2) a conscious experience of an event or situation (such as anger); 3) a physiological expression (such as paleness, blushing, palpitations, and feeling of unease). It is not clear how these three processes are related.

According to Squire and Kandel (2000), emotional reactions occur in both a conscious and an unconscious manner. Conscious reactions to different situations depend on conscious thinking. However, unconscious reactions of emotions to different situations are independent of conscious thinking. For instance, consider a woman who had a traumatic experience with a hot stove at a young age and now reacts strongly towards stoves. Squire and Kandel explain that:

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[5] Differences between emotion and feeling and their functionalities are broad topics that go beyond the scope of this thesis. Damasio (2003) described emotions upon their physiological effects. Accordingly, feelings are situated in the body and emotions consistently result from them. For this study, as we are not going to discuss physiological aspects of emotions; we will consider feeling only in its perceptive role of emotional states in an agent.

> "The feeling is a memory to be sure, because it is based on experience but it is unconscious, nondeclarative and independent of the capacity for conscious recollection. Because the feeling about stoves and the conscious remembering of what happened are parallel and independent, the existence of this unconscious memory, a fear of stove is no guarantee that the young women can access a declarative memory to explain how the fear came about. The original event may be consciously remembered or it may have been forgotten (p.171)."

2.1.1 Psychological theories of emotional organization

Scientists proposed different methods for the organization of emotions and their relations to one another. Three are briefly explained in the following.

1) Categorical theory (Izard, 1977, Plutchik, 1980, Lang and Sumner, 1990). Emotions are viewed as distinct entities and divided into "basic" and "complex" emotions. Basic emotions are considered as innate, evolutionarily ancient and are thought to be common in different cultures. In contrast, complex emotions are learned, evolutionarily new, influenced by language and shaped within an individual's society and culture. However, there is no consensus on what could be considered as a basic emotion, and on what complex emotions are;

2) Dimensional theory (Russell, 1980, Lang et al., 1993). Two important elements of this model are arousal and valence. Given a situation, arousal is defined as the emotional intensity to respond to the situation and valence is our positive or negative feeling towards the situation. To demonstrate arousal and valence scientists propose two models (Figure 2.1.A): **a)** A vector model, where the two vectors form a boomerang shape. The upper vector shows positive valences and the lower vector shows negative valences. The arousal start from a neutral endpoint that initially are considered as low and continue on upper and lower vectors which are equivalent to positive and negative vectors until high levels of arousal; **b)** A circumplex model (Figure 2.1.B), where two intersecting orthogonal lines are bounded by a circle and the neutral point is situated in the center of the circle. The horizontal line shows arousal and changes between low (calm) to high (excited). The vertical line shows valences that go from pleasant to unpleasant. The resulting graph categorizes and put similar emotions in the same range. However, the dimensional theory ignores the crucial link between the current emotion and the prior intentional states of the individual. The theory also ignores the causal relationship between individual interpretation (appraisal) and emotion (Marsella et al., In press);

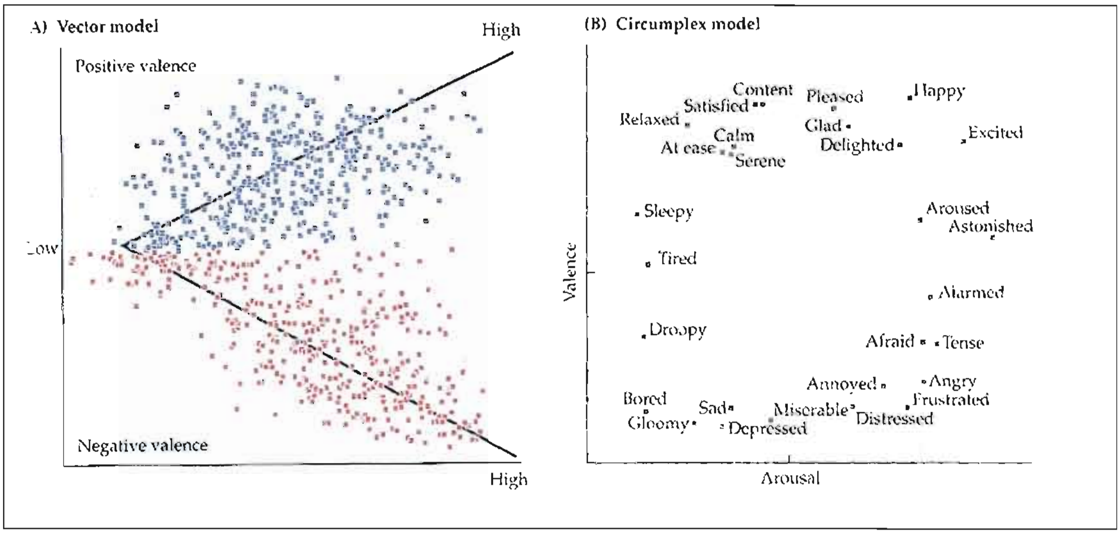

Figure 2.1 Dimensional theories of emotion: the vector (A) and circumplex (B) models (from of Purves et al, 2008)

3) Component theory (Scherer, 1987). Contrary to the Categorical and Dimensional theories, which consider emotions as independent entities, this theory is based on "appraisal" approaches and describes various flexible characteristic of emotions. Appraisal is described as a cognitive interpretation of what we sense or perceive. Furthermore, the theory explains our evaluation of specific external (for instance environment) or internal (about ourselves) stimuli that cause emotions (Roseman and Smith, 2001). Roseman and Smith (2001) explained that our motives and goals play an important role for the evaluation of a specific situation. Given that we can evaluate what we observe and cannot decide how we observe things in our environment, the appraisal theory could be used to explain the autonomic reaction of emotions in human when faces to a particular situation Different computational models are proposed. In the following paragraphs, we briefly describe two important computational models based on the appraisal theory:

1) **The OCC Model (**Ortony, Clore, & and Collins, OCC): One of the most complete and widespread computational model used in artificial intelligence is the OCC model (1988). The model considers emotions as "valenced reactions to the external or internal stimuli based on the manner in which the situation is interpreted."(Ortony et al., 1988). Three specific types of stimuli are defined by this model: event consequences, agents' actions, objects situated in the environment. Received stimuli map to a positive or negative value, via an "appraisal" or "assessment" process. Upon the emergence of emotion, it influences the agent's cognitive process in different fashions. The behaviour, in this model, is considered as a response to an elicited emotional state, which is in relevant to the received internal or external stimulus. OCC model has categorized 22 emotions into three main classes: 1) emotions that correspond to objects such as liking (love) and disliking (hate) them; 2) emotions that are consequences of events such as being pleased or displeased- these include well-being (e.g. joy, distress), prospect-based (e.g. hop, relief, fear), fortunes-of-others (e.g. happy-for, resentment, gloating, pity); 3) attribution compounds which includes pride, admiration, shame, and reproach. The emotion's intensity relies on the internal and external stimuli the agent receives from the environment. In some cases, the OCC emotional model is also integrated with a personality model that include goals, sets of behaviour and way of thinking (Atkinson et al., 1983).

However, the OCC model did not discuss emotion intensity in detail (Adam, 2007). There is no clear description of how the model assigns the agent's emotional states to behaviour. Given the OCC model's complexities, it must be simplified before integrating it to the cognitive agent's architecture. The model initially ignored surprise, but others added it later to the model. The model is not equipped with a history function because likelihood is essential to estimate the desirability for a given situation to the agent (Bartneck, 2002).

2) **The Lazarus model (Lazarus, 1991)**: In this model, the constant cycle between components of the model functions in the following manner: person-environment interactions incite appraisal variables in the person, which leads to the generation of affective answers that occur with some intensity and which will set off behavioural and cognitive outcomes (Lazarus, 1991, Marsella et al., In press). The important parts of the theory are: (1) the fact that the appraisal is the assessment given by an individual to various situations according to his/her beliefs, desires and intentions. Appraisal variables in this theory are particular assessments given by an individual to generate specific emotional answers; (2) the fact that coping has to do with how to react to an appraised event. For instance, feeling pain in an individual facing a specific situation (appraisal), may cause the generation of guilt (coping) which may lead to an annoyed state in the individual (re-appraisal).

The comparison between the OCC and the Lazarus model follows. While the OCC model covers a wide variety of emotions, Lazarus proposes a more precise description of appraisal variables to differentiate different emotions. However, the Lazarus model excludes some emotions considered in the OCC model, such as admiration, reproach, remorse, etc. (Adam, 2007).

2.1.2 The generation of emotions: neurobiological and cognitive aspects

In this section, we explain that both physiological and cognitive activities are important for the generation of emotions. Following Ledoux (2000), we take it that the amygdala subserves an additional memory system, which we call emotional memory. But the amygdala's involvement in learning and memory goes beyond emotional memory, as it also modulates learning in other memory systems, especially declarative memory (Schoenbaum et al., 2000). Squire & Kandel (2000) explain that:

> "The amygdala and the hippocampus systems independently support non-declarative memory and declarative memory. The two systems can work

> together. Animals retain a task more strongly, when a variety of hormones such as adrenaline are injected into their blood and brain after they learn to perform a task. The enhancement of memory by emotion results from the amygdala's influence on declarative memory (P. 171-172). Other experiences also show that the more active the amygdala is at the time of learning, the more it enhances the storage of those declarative memories that had emotional content (p.173)."

Accordingly, we describe two general types of emotional learning: pure emotional learning (i.e., learning subserved by the amygdala), which gives rise to emotional memory proper, and emotionally modulated learning (learning subserved by hippocampus and cortex (see below) but that is modulated by the amygdala), which brings about other types of memories, and infuses them with emotional content. Each of these types of emotional learning corresponds to a specific pathway to the amygdala. The first route, the short-route, is based on peripheralistic concepts from James' work (James, 1884). It is short and direct (bold arrows in Figure 2.2); information flows from the sensory thalamus directly to the amygdala (Figure 2.2, bold arrows) and then projects to particular structures such as the basal ganglia. The short route enables implicit (i.e., unconscious) direct behavioural reactions based on previous rewards or punishments associated with the same or similar stimulus (Squire and Kandel, 2000, Rolls, 2000). Human reactions are then rapid and unconscious (Squire and Kandel, 2000), because the reaction is dependent on information that is not processed by other brain structures, notably cortical structures. For example, if, while walking in a forest, we encounter a long and sinuous cylinder-like object close to our leg, we will in general react very quickly and, without thinking, move our leg away from the object. In this case, information from the retina entered the sensory thalamus, which passed the information along to appropriate cortical structures for further analysis. But the signal was also sent to the amygdala, which recognized the possible danger posed by the perceived object posed and sent a signal to the motor system for immediate movement of the leg, away from the object.

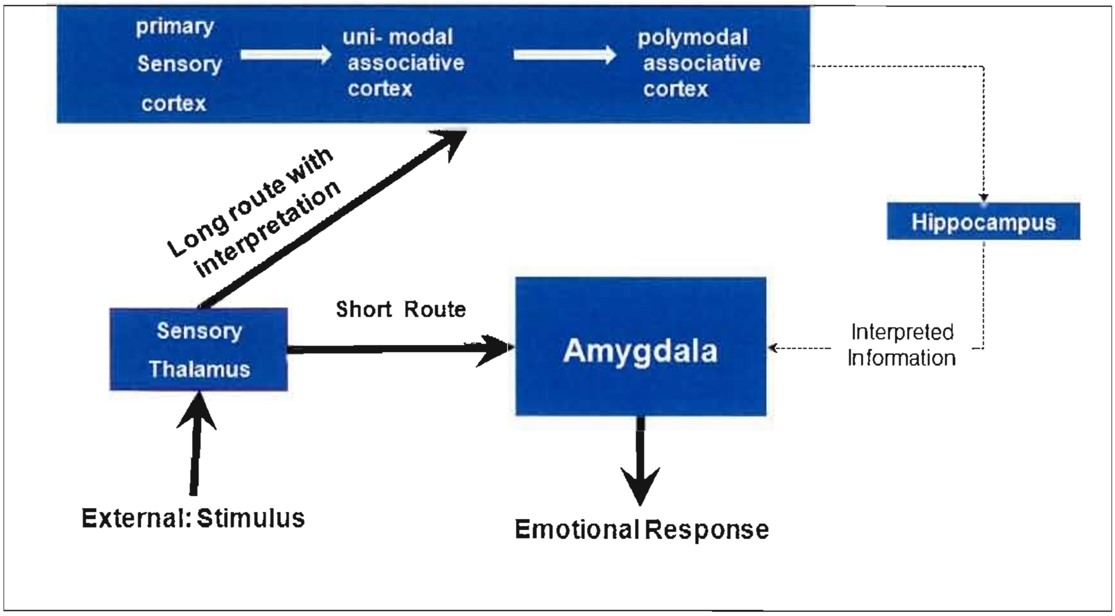

Figure 2.2 The short route from sensory thalamus to the amygdala

In the second route, based on centralistic concepts originating from Cannon's work (Cannon, 1927), (bold arrows in Figure 2.3), information from the external environment is analyzed by various cortical areas (primary sensory cortex, unimodal associative cortex, polymodal associative cortex). It is then sent to the hippocampus, for memory retrieval and temporary storage. All this processing serves to interpret the external stimuli, to give it meaning (categorization by the cortex) and link it to other events in episodic memory (see below), before it goes to the amygdala for emotional appraisal and response. In our previous example, this longer route would correspond to the recognition, for instance, that the object we moved our leg away from is not a snake after all but a peculiarly twisted piece wood, and the remembrance of previous forest walks in which we saw tortuous branches. Although it is slower, the response produced by this second route possesses the normal phenomenology of thoughtful behaviour and can be consciously controlled. Once it has been interpreted by cortical structures the information then flows back to the amygdala where can serve to reinforce or correct its initial processing of the information.

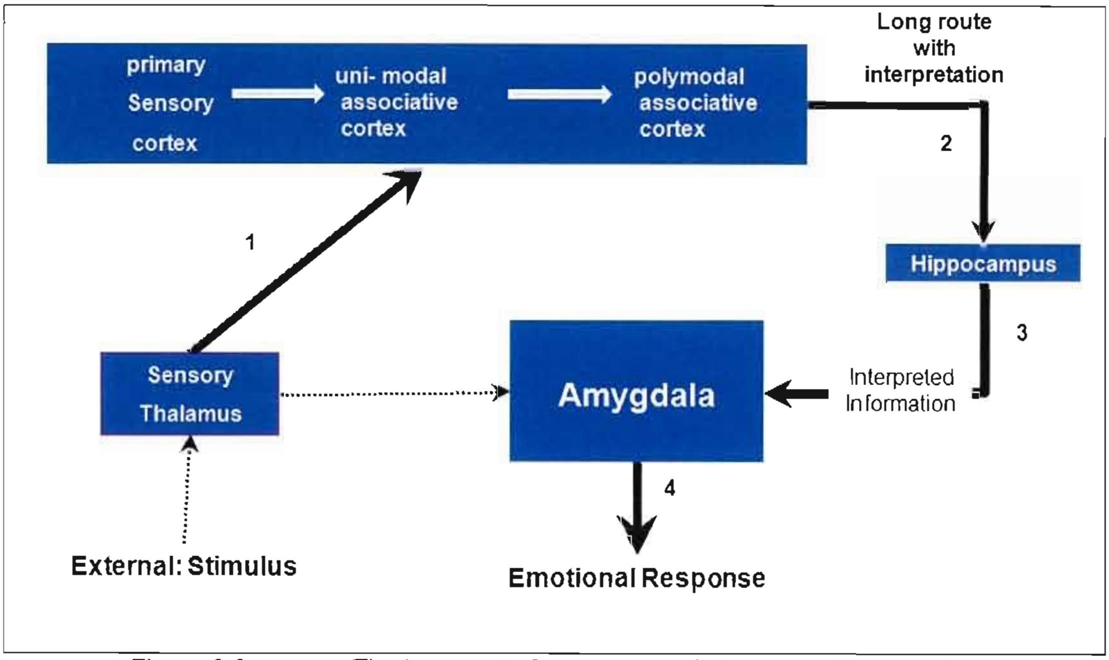

Figure 2.3 The long route from sensory thalamus to the amygdala

2.1.3 Emotional Learning

For evolutionary reasons, it is sensible to believe that we are born with automatic emotional responses to some stimuli (e.g., snakes and spiders). Moreover, work by Joseph Ledoux (LeDoux, 2000, LaBar et al., 1998, LaBar et al., 1995) and others (Pribram et al., 1979, Rolls, 2000, Schoenbaum et al., 2000) has shown that the amygdala can learn to react to novel stimuli. It is known that if a shock is paired with a tone, the tone will come to elicit the fear reactions originally elicited by the shock. More generally, if a neutral stimulus is paired with an unconditioned stimulus that elicits a fear reaction, then fear will become the conditioned response to the previously neutral stimulus (which has now become a conditioned stimulus). Fear conditioning has been shown to be mediated by the amygdala (especially the Lateral (LA) and Central (CE) nuclei of the amygdala, see (LeDoux, 2000). Such learning takes the short route to the amygdala. In cases where the stimulus is auditory (such as a tone), information flows from the medial geniculate body directly to the lateral nucleus of the amygdala (LA) and then to the amygdala's central nucleus (CE) from where it goes to the brain stem for the expression of fear responses. Such responses are quick, and it is reasonable to believe that they are automatic and unconscious.

Through the long route, the amygdala receives inputs from the later stages of sensory processing but sends its outputs to early stages of sensory processing (Squire and Kandel, 2000, Purves et al., 2008, Rolls, 2000). This means that the amygdala can affect sensory processing in the cortex from its early stages. No sensory information in the cortex is left untouched by the amygdala's influence. Moreover, the amydgala also affects all cortical processing indirectly through its effects on arousal systems that innervate large areas of the cortex (the basal forebrain, the cholinergic system, the brainstem cholinergic system, and the locus coreuleus noradrenergic system). With these, the amygdala can also influence the cortex through feedback from proprioceptive or visceral signals or hormones. The amygdala can thus be seen as having a large influence on cortical processing, including learning, which we will model here by the emotional valence (positive or negative) the amygdala adds to sensory processing.

In the next section we will explain different types of memories and how emotions influence them.

2.2 MEMORIES

Most researchers agree that memory is the process of acquiring, storing and retrieving information and this information may alter our behaviour. Memory is considered to lay in physical and biochemical processes in the brain (Thompson and Madigan, 2007, Moxon, 2000).

Thus, one major role of memory is to keep record of what happened in the past.

Neuroscientists have distinguished four major memory processes: 1) encoding, which is how experiences cause the creation of memory traces; 2) retrieval, which is the way that the brain restores memory traces; 3) consolidation, which is how after the encoding phase, the memory traces may get reinforced; 4) storage of information, which concerns the endurance of the information.

The encoding and retrieval processes are measurable by observing human behaviour. For instance, we remember best what we are familiar with. However, the consolidation and storage processes are only measurable using special cognitive neuroscience methods and instruments that are capable of monitoring neural processes. Neuroscientists postulate that all types of memories rely upon the same cellular mechanisms of synaptic modification for storage. However, encoding and retrieval of different memories (for example declarative and non-declarative) rely upon different brain regions (Purves et al., 2008).

The two following theories regarding memory functionalities were put forth by cognitive psychologists: 1) record-keeping theory, 2) constructionist theory;

1) Record-keeping theory. Memory is considered to be an item-filled box. Like a computer disk, each experience becomes a new record. Various indexing methods are used to sort information. Indexes are used during the recall phase. When the amount of stored information is too large, there is memory interference and forgetting occurs (Guenther, 2002). The record keeping theory is used by scientists who use computers as a metaphor to explain memory functions (Guenther, 2002).

2) Constructionist theory. Human memory is considered to be dynamic and dependent on the context at any given moment. Its purpose is not only to allow recollection of the past, but also to assist in anticipating the future. It has been shown that when we witness a crime or accident, we may later recall details that never were. In 1979, Loftus conducted a study where subjects were shown a car accident scene. Later subjects were asked questions about the accident with words such as *smashing* and *bumped*. Given the influence of the words used, subjects wrongly recalled that the car's window was broken during the accident (Donderi, 2005). Thus, new information alters human cognitive systems such as emotions, perception, interpretation, etc. Memory is influenced by the environment. Remembering in this theory is not just searching through registered records from the past experiences; it is, rather, the regeneration of past experiences. It is a dynamic process. Memory is influenced both by the cognitive system in interaction with its environment, and one's load of past experiences. Forgetting is due to the interference that new and constant changes bring to our cognitive system, as well as the adaptations that our cognitive system undergoes (Guenther, 2002).

2.2.1 Different types of memories

It is now near consensus that the brain contains multiple memory systems, however few agree on how to categorize them (Squire, 1992). What follows are the most important according to the majority of the scientists (see Figure 2.4):

1) **Sensory memory**: it is what our perception mechanisms briefly record and which disappears in less than a second;

2) **Short-term memory**: it depends on the attention brought to particular items in function of the sensory memory (decays in less than a minute). These units are called chunks and vary from individual to individual. Repetition is crucial for information storing in short-term memory- phone number memorization, for instance. This process is called rehearsal. The information in short-term memory interacts with sensory memory input and long-term memory;

3) **Working memory:** cognitive processes such as reading or writing are applied to items momentarily stored up in this memory. Working memory can store from five to nine information units. Scientists believe that short-term memory cannot be considered as the only temporary memory that contains long-term memory items. It must be noted that, nowadays, scientists do not consider a distinct line between memories and thought (Squire and Kandel, 2000)

The two principal working memory models proposed are Baddeley's model and Cowan's model (Baddeley et al., 2002, Cowan, 2005). *Baddeley's model* suggests that different regions of the brain are involved in the storage of working memory and long-term memory. In this model working memory is divided into three delimited memory buffers and a central executive controls unit that controls the operations of the three buffers: the phonological loop, the visuospatial sketchpad, and the episodic buffer. The phonological loop interacts with the long-term memory's component that is related to our language capabilities. The visuospatial sketchpad interacts with the long-term memory's components that contain visual semantic information. The episodic buffer interacts with the long-term memory's component containing episodic memory information.

Buffers are equipped with storage and rehearsal mechanisms. The task of the store mechanism is to save the information temporarily in the buffer. The task of the rehearsal mechanism is to reactivate the temporarily saved information in the buffer before it disappears. Baddeley's central executive unit operates the memory buffers, determining the focus of attention.

Cowan's model postulates that working memory and long-term memory both rely on the same types of representations. In this model, in the first step, different regions of the long-term memory activate temporarily – there is no limit for the activation of the regions. In the second step, the attentional focus dictates which region must remain active, thus causing the dissipation of other activated regions that have not received attentional focus;

4) **Long-term memory:** it is divided in two broad classes: a) **explicit (declarative) memory,** subserved by the medial temporal lobes (hippocampus is the key component of this region), frontal and parietal lobes area, and sensory regions of the brain; b) **implicit (non-declarative) memory,** subserved by the striatal system (Squire and Kandel, 2000). What distinguishes short-term memory and long-term memory is the duration of information processing. Short-term memory is used by brain to maintain the information for a short period of time while long-term memory is the acquisition and recovery of the information related to a longer period.

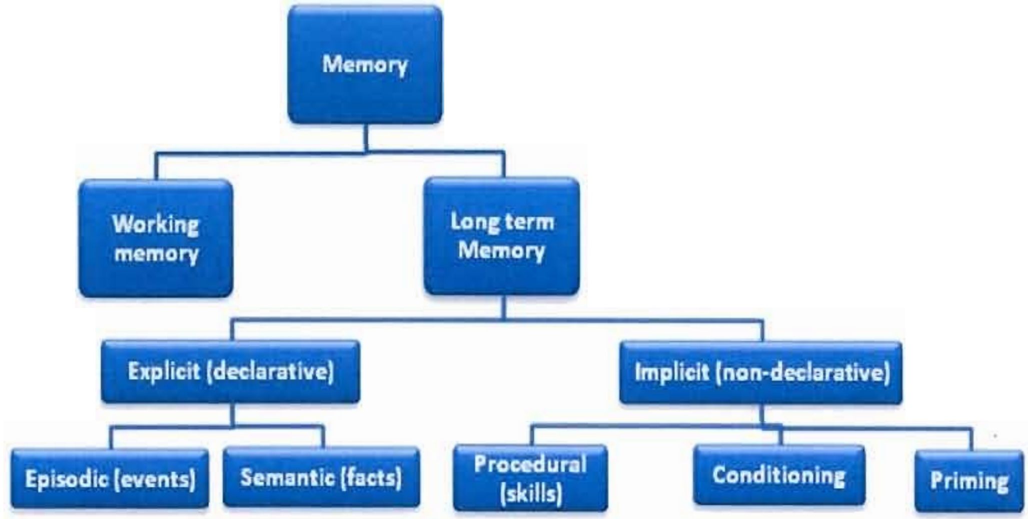

Figure 2.4 Long-term memory structure (Tulving, 1972, Tulving, 1983, Squire and Kandel, 2000)

Explicit (declarative) memory: it refers to the memory of facts and events. The content of explicit memory, when needed to be retrieved and manipulated, requires consciousness. Explicit memory is divided into **a) semantic memory**: the general knowledge or facts such as "*what is the meaning of amendment*? " (Tulving, 1972, Tulving, 1984). We do not remember when we learned the content of semantic memory; **b) episodic memory**: the memory of what, where and when (e.g., what you ate yesterday). Episodic memory is the memory of particular events. It also allows people travel back through time mentally and imagine the future (Tulving, 1972, Tulving, 1984).

Episodic memory is closely linked to semantic memory (similar episodes over time). Neuroscientific evidence has demonstrated that sometimes, during the encoding phase of episodic memory and the remembering phase of semantic memory, several of the same brain's regions are activated - the overlapping phenomena occurs in the left inferior frontal gyrus region(Purves et al., 2008).

Autobiographical memory, which refers to our own life's events, results from a complex collaboration between episodic and semantic memory. For instance, one's semantic memory information of the Persian New Year in Shiraz may be influenced by our information that Persepolis is located in Shiraz, and that the very famous statue of King Darius is located there, and that the place is very crowded. All these semantic memories may influence our rebuilding of our episodic memory of the Persian New Year during a stay in Shiraz. Taking in one level further, we may also remember episodes that we learned during a prior discussion with friends about Persepolis (Williams et al., 2008, Conway and Pleydell-Pearce, 2000, Conway, 2005).

Implicit (non-declarative) memory: The implicit memory, when needed to be retrieved, is unconscious and is expressed through our behaviour. It includes: 1) **procedural memory**: it refers to "how to" knowledge of procedures or skills, for instance swimming; 2) **conditioning**: when humans create an "*association between different stimuli and between stimuli and responses*"; 3) **priming**: when humans react more easily to previously seen stimuli (LeDoux, 2000, Purves et al., 2008, Squire and Kandel, 2000).

All three aforementioned non-declarative memories are independent of the medial temporal lobe in human.

2.2.1.1 Episodic Memory Consolidation

Two models are suggested in neuroscience for the memory consolidation phase (Purves et al., 2008).

1) The standard consolidation theory, which holds that the result of event encoding are hippocampus-independent. It posits that the hippocampus performs a fast interpretation and learning of a given concept or event. In the transfer phase, indirect connections are thought to be created between the hippocampus and various neurons in the cortex. The hippocampus then distributes these memory traces to the cortex. Importantly, in this model, the cortical neurons representing events create direct connections between themselves and gradually become independent of the hippocampus.

2) The multiple-trace theory, the multiple-trace theory, on the other hand, holds that the results of event encoding are hippocampus-dependent. According to this theory, every time an event causes memory reactivation, a new trace for the activated memory is created in the hippocampus. Memory consolidation occurs through the reoccurring loops of episodic memory traces in the hippocampus and the construction of semantic memory traces in the cortex. Thus, the cortical neurons continue to rely on the hippocampus even after encoding.

2.2.1.2 Episodic memory retrieval

Given a particular situation in which I was asked to think about the dinner I had of last year at Christmas Eve, what came to mind is described below:

That night, I was invited to go out for dinner with my friends, but I had to finish writing a scientific paper. Thus, I had cancelled the rendez-vous with my friends and prepared an omelette with a piece of bread on the kitchen table and started to eat. I had also prepared a hot chocolate which I really like to drink every afternoon. Hmm, No... I did not have the omelette because my friends came in while I was preparing dinner. Then, they asked me to stop working and took me out to a nearby restaurant for dinner. For dinner, we had turkey with some potatoes. I also had a hot chocolate.

In this example, a retrieval cue (the question about dinner), first, sets off memory search processes to restore specific memory traces related to the situation's particular features such as time and place (last year's New Year's eve, the lab, and a restaurant). What are restored as memory traces (omelette, bread, hot chocolate) will be evaluated by monitoring process. The monitoring process may refine/reject or accept restored memory traces from long-term memory (stop eating omelette and go out for dinner). During episodic memory retrieval processes, attention remains fixed on this particular situation's features.

Emotions affect different types of memory and enhance learning in humans. Indeed, it has been shown to be in part responsible for our emotional reactions in the enhancement of episodic memory (Hamann et al., 1999, Dolan et al., 2000a, Paré, 2003). Because emotions and episodic memory play two complementary roles in learning and in the retrieval phase, we argue that both must be included in cognitive architectures.

2.2.2 Reasoning and Causal Learning

Reasoning is considered crucial for many characteristics of cognition such as selection, abstraction, planning, etc (Gopnik and Schulz, 2007, Sarma, 1993, Leighton, 2004, Demetriou, 1998). Reasoning begins with an initial state, a goal and a set of possible operators. To achieve the goal set in the initial state, one may be faced with several intermediate obstacles. This makes establishing a direct path between the initial state and the goal difficult. The term *reasoning* is used in situations in which rules are clearly identified and possible actions are highly restricted. The term *problem* solving is used in situations in which the rules are unclear and we face a large number of possible actions. To solve a problem, we can use the trial-and-error approach. As opposed to reasoning, the trial-and-error approach does not imply deliberation and a rational approach (Woll, 2001, Goswami, 1998).

The three types of reasoning we focus on in this work are the following:

1) Deductive reasoning, where one logically decides the conclusion from a general rule. Moreover, in deductive reasoning, the truth of premises assures the truth of conclusions and the relation between Premise and Conclusion is certain (Kemerling, 2005). For example, in math:

If $x=2$ and $y=3$ Then $4x+y= 11$

Deductive reasoning is nonampliative – i.e., cannot actually extend our knowledge. Thus, in deductive reasoning, despite observing and making specific conclusions, one cannot predict unseen situations (Russell and Norvig, 2003, Sternberg and Mio, 2009).

2) Inductive reasoning, where either one tries to generalize rules from a set of examples, or, on the other hand, from a set of probable or inadequate premises, one decides the likeliness that a conclusion is true. The truth of a conclusion is likely when the premises give some evidence or support towards the conclusion. In inductive reasoning, when evidence is deemed to be absolute, significant, and generally persuasive, they are cogent. They may bring us to a true conclusion. When the evidence is not deemed absolute, significant and persuasive, then the evidence is non-cogent. In inductive reasoning, the relation between premise and conclusion is uncertain. After generalization, one cannot claim that all potential information about a situation has been collected and that there is no additional unseen information that could discredit the hypothesis. For instance consider the following example. From the statement "The football moves when kicked by a player," we can infer "All footballs move when kicked by a player." The inductive reasoning is ampliative – it extends our knowledge. One usually needs to examine prior knowledge, relation, set of examples and experiences in order to draw inductive conclusions from premises. However, all this information that one must examine to come to a conclusion from a set of premises makes it difficult for scientists to propose a universally accepted theory of inductive reasoning (Russell and Norvig, 2003, Feeney and Heit, 2007, Sternberg and Mio, 2009).

3) Abductive reasoning, where one tries to give an apt explanation from a set of observations (inference to the best explanation). Abductive reasoning sometimes plays a very important role in decision-making when the information is not sufficient. Abductive reasoning is described by incompleteness in evidence and/or explanation. For instance, in the case of an airplane crash, when experts examine the accident scene, some crucial evidence may be missing. The experts' explanations about the accident may be flawed due to this missing information. Likewise, a computer that is not capable of correctly reporting a malfunctioning problem in hardware or software will only provide some incomplete predefined messages. Technicians will likely be unable to fully explain the nature of the problem (Sebeok, 1981).

2.2.2.1 Causal Learning

Among the various aspects of inductive reasoning, researchers investigate the existence of causal relations between various events (Kemerling, 2005). We assume that there is a particular cause to a particular effect, only, by observing the occurrence of regularities in some particular events. Hume suggested that our beliefs and feelings[6] also play an important role when we develop a causal relation between events (Kemerling, 2006). Scientists use the experimental approach to establish the causes between events. Knowing causes, we can change the outcome of situations. To do so, we have to find relations between events, and how some events affect others. We can learn to make inferences, but the result may depend on prior knowledge, experience, and how well these are mastered. It may also depend on the individual's interpretation abilities. For instance, one may infer that coffee is the cause of our current abdominal pain after observing that drinking coffee is always followed by such pain. However, causal relationships between events do not provide us the absolute proof since there may exist some unidentified aspects. For instance, we know that some people suffer from schizophrenia, but we do not know the causes yet.

Abū Alī Sīnā (Avicenna) proposed three methods for finding causes (Goodman, 1992, Goodman, 2003). John Stuart Mill added two additional methods (Kemerling, 2002). We explain them through an example. Suppose that in a company, some employees spend their break together and each time they drink some beverages. After a while, a number of employees report abdominal pains each afternoon. Thus, they suppose that the problem comes from what they drank. To find

[6] Feeling: "the perception of a certain state of the body along with the perception of a certain mode of thinking and thoughts with certain themes." Damasio (2003)

which beverage causes abdominal pains, Avicenna and Mill's five methods would be used in the following manner:

1) **The method of agreement.** Imagine three of employees have abdominal pain and discuss about the cause of the pain. The first had apple juice, orange juice, and a coffee; the second had a grapefruit juice, coffee, and iced tea; the third drank iced tea, hot chocolate, and coffee. From this information one can conclude that coffee is the cause of abdominal pain. In all three cases, only one circumstance led to having pain- coffee.
2) **The method of difference.** Now supposing that the first employee drank an apple juice, orange juice, and a coffee, while the other drank apple juice, orange juice, and hot chocolate. In this case, the one who drank coffee has abdominal pain. Again we can conclude that the coffee is the cause of abdominal pain. Thus, in this method one tries to detect which possible causes were present when the abdominal pain occurred, and were not present when the effect (abdominal pain) did not occur.
3) **Agreement and difference.** Given the two previous situations, suppose that two employees drank different sets of beverages, and that only the one that drank coffee had abdominal pain. Suppose also that two other employees drank different sets of beverages and that only the one who had coffee had abdominal pain. Since all those who drank coffee had abdominal pain and none of those who drank something else were sick, we conclude that 1) only coffee and 2) nothing else causes abdominal pain.
4) **Method of Concomitant Variation**. Now, supposing that out of the four employees, the first one didn't have coffee and felt no abdominal pain; the second had one cup of coffee and felt ill; the third had two cups of coffee and felt abdominal pain; and the fourth had five cups of coffee and had to go the doctor. We can again conclude that the coffee caused the abdominal pain. With this method, we are not just faced with the occurrence and non-occurrence of causes and effects; we observe that intensifying the cause is related to increasing the extent of the effect.

5) **The method of residues**. Finally, supposing that another doctor came to the conclusion that hot chocolate is likely to be the cause for dental problems and chamomile the cause for sleepiness. Today, an employee arrives and complains about dental problems, abdominal pain, and sleepiness. He also lists hot chocolate, coffee, chamomile and orange juice as what he drank during the day. Knowing the cause of dental problems and sleepiness, the doctor can conclude that the hot chocolate must be the cause of toothache. The example demonstrates the creation and combination of probable causes.

These methods have some flaws when it comes to apply them in scientific research applications, as, for a given situation, we are not always capable of considering every possible condition leading to a particular effect. Thus, the five aforementioned methods are not useful when it comes to unidentified causes' of an event (Kemerling, 2002).

Scientists propose causal Bayes nets (acyclic graphs) as an alternative approach to establishing causal relation between events. The key concept for the construction of a causal Bayes net is finding *conditional probability* between events. Mathematic is used to describe conditional and unconditional probabilities between a graph's variables. The structure of a causal graph restricts the conditional and unconditional probabilities between the graph's variables. We can find the restriction between variables using the Causal Markov Assumption (CMA). The CMA suggests that every node in an acyclic graph is conditionally independent of its ascendants, given the node's parents (direct causes). For instance, suppose one observes that each time one forgets to adjust his car's side and front mirrors (M), he tends to have poor control over the wheel (W) and cause collisions (C) with other cars. We can link these variables in the following way: (1) $M \rightarrow W \rightarrow C$; and (2) $W \leftarrow M \rightarrow C$. The first graph (1) shows that the probability of forgetting mirror adjustment is independent of the probability of making collision with other cars, conditional on the occurrence of poor wheel control. The second graph (2) demonstrates that the probability of poor wheel control is independent of the probability of making a collision with other cars and is conditional on forgetting mirror adjustment. The CMA establishes such separation between nodes to all acyclic graphs' nodes. Thus, knowing a graphs's structure and the value of some variables' values, we are capable of predicting the conditional probability of other variables. Causal Bayes nets are also capable of predicting the consequences of direct external interventions on their nodes. When, for instance, an external intervention occurs on a node (N), it must solely change its value and not affect other node values in the graph except through the node N's influences. In conclusion, one can generate a causal structure from sets of effects and conversely predict sets of effects from a causal structure (Gopnik and Schulz, 2007).

Recent studies in neuroscience have demonstrated the role of the prefrontal cortex in inductive and deductive reasoning (Goel and Dolan, 2004). These suggest that in an individual, the creation of new hypotheses in inductive reasoning essentially activate the left prefrontal cortex (LPFC). Given the fact that left prefrontal cortex activation is crucial in inductive reasoning, we assume that the same region in our brain is also crucial for causal learning.

2.3 CONCLUSION

The nature of emotion, its emergence and how it influences cognitive process remain controversial. This, because emotions are simultaneously required in different processes such as cognitive, biological and physiological, etc. This has lead to various definitions addressing specific aspects of emotions, with none addressing emotions as whole.

One important part of cognition is memory. In humans, all memories are influenced directly or indirectly by the amygdala, which play a major role in emotional processes. In fact, human decision-making, reactions and learning are under the influences of emotions and feelings (Bower, 1992, Dolan et al., 2000b, Purves et al., 2008, Squire and Kandel, 2000). For instance, Cándido (Cándido et al., 2006, Maldonado et al., 2007) demonstrated how emotions of different affective valences can bias causal learning.

My goal in this study is to propose and implement an emotional mechanism in a cognitive agent based on neuroscientific evidences. In our model, the emotional mechanism is capable of learning and influences different types of learning and decision making. I also propose a generic method for the implementation of episodic and causal learning in cognitive agents and how they are influenced by the proposed emotional mechanism.

CHAPTER III

EMOTIONS AND LEARNING IN COGNITIVE ARCHITECTURES

Most researchers in computer science agree that the concept of autonomy is essential to the definition of an agent (Franklin, 2006, Wooldridge, 1999, Franklin and Graesser, 1997). Franklin (1997) defined an agent as "*a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future.*"

Russell calls such an agent intelligent[7] (Newell and Simon, 1976) (Russell and Norvig, 2003). The key concepts in the definition given by Franklin is that an agent must be a dynamic part of the environment, sense it, act on it in an autonomous fashion; it must have temporal continuity. This occurs when an agent has sensors to sense the environment, effectors to act on the environment, and primitive motivators to motivate its acts (Franklin, 2006). For instance, an antivirus is installed on a computer and must react each time a program is executed and is pre-programmed to check the computer to find viruses at mid-night. In addition, an agent must learn from its environment and adapt to changes. Thus, being adaptive and able to learn is one of the very important properties of an agent. Learning, in an agent, must be incremental and continual (Franklin and Graesser, 1997). Wooldridge (Wooldridge

[7] Newell and Simon's Physical Symbol Systems theory suggests that a physical symbol based system is a necessary and sufficient condition to produce a general intelligent action.

and Jennings, 1995, Wooldridge, 1999) has categorized agents into the following types:

1) Reactive: A purely reactive agent is one whose action depends only on what it perceives at the present moment. Such an agent does not store any internal information. Neither does it consider the history of its previous actions when making decision.

2) Deliberative: These agents are capable of monitoring their environment and acquire an internal representation of it. They are capable of generating plans to meet their goals.

3) Hybrid: These agents have a composite behaviour of reactive and deliberative agents in that they are capable of generating new plans and respond immediately to external stimuli.

A cognitive architecture is a prototype for the design of intelligent agents (Langley et al., 2008). In the following section, we very briefly explain cognitive architectures.

3.1 COGNITIVE AGENTS

The nature of cognition, the role of cognitive systems and the way they function are topics too broad and out of the scope to be covered in this study. It is agreed that if a system were endowed with cognition, it would have the following capabilities: learning, adaptation, anticipation, autonomous behaviour, natural language, creativity and self-reflection (Brachman, 2002, Hollnagel and Woods, 1999, Freeman and Nunez, 1999, Anderson and Lebiere, 2003). In this study, we also propose self-satisfaction as an important capability of cognitive systems (Faghihi et al., 2009b). This will be explained in the episodic learning (see section 4) part of this text.

Cognitive systems (agents) are divided into three type (Vernon et al., 2007): 1) cognitivist; 2) emergent; 3) hybrid.

3.1.1 Cognitivist approach to agents

Cognitivist scientists use symbol[8] manipulation to study cognition (Newell, 1990, Newell and Simon, 1976). This theory defines explicit symbolic representation mechanisms to allow systems to reason about the external world. Information about the external world is abstracted by perception and represented using a symbolic framework. Then, symbols are interpreted and reasoned in order to plan an act in the external world. Cognitivist scientists postulate that symbol manipulation processes equip cognitive agents with the necessary tools to easily and efficiently adapt and interact with the external world, predict the future and use reasoning capabilities. Different methods such as machine learning, probability approaches and logical rule-based approaches are used to implement cognitivist systems. In these systems, symbol representation is the product of human work, which means that there is a direct access to semantic knowledge. However, such a system is limited to the predefined descriptions and conditions (Winograd and Flores, 1986).

Given Newell's hypothesis that human beings use symbols to represent abstract concepts (Newell, 1990), a cognitive architecture must be able to combine symbols ("chunking") in order to facilitate their subsequent uses. As in the human brain, cognitive architectures should work with, among others, emotional learning, episodic learning and procedural learning. Ron Sun later proposed a definition for the two coexistent processes of explicit/implicit knowledge (Sun, 2004). Explicit processes refer to factual, declarative or non-procedural knowledge to which

[8] Newell and Simon: "Symbol systems are collections of patterns and processes, the latter being capable of producing, destroying, and modifying the former. The most important properties of patterns is that they can designate objects, processes, or other patterns, and that when they designate processes, they can be interpreted. Interpretation means carrying out the designated process. The two most significant classes of symbol systems with which we are acquainted are human beings and computers."

consciousness has access, such as the abstract idea that the moon turns around the earth. Implicit processes refer to the procedural knowledge to which consciousness has no access to, such as knowing how to swim.

3.1.2 Emergent approaches to agents

In the emergent approach, scientists state that cognition is the construction of skills through a self-organization process (behavioural / configurational emergence) in which systems interact in real time with their environment. This reminds us of the importance of embodiment for the construction of knowledge. Embodiment is a practical and social phenomenon necessary for the construction of meaning (Anderson, 2003). For an agent in the real world, perception and representation are mostly constructed via the agent's physical movements (Ziemke et al., 2007) (de Vega et al., 2008). According to Anderson (2003), embodiment plays an important role in shaping cognition in four areas, namely: physiology, evolutionary history, practical activity, and socio-cultural situatedness. Thus, the emergent approach is opposite to: 1) the dualism theory that asserts separation between body and mind; 2) functionalism that views mind as only existing based on its fulfilling its role, its functioning. Thus, any entity that produces the same output as the mind in a given situation, should, according to functionalists, be considered to be a mind, regardless of the entity's nature.

In what follows we explain emergent systems. Emergent systems encompass connectionists, dynamical, and enactive systems (Varela, 1992, Clark, 2001).

3.1.2.1 Connectionist systems

Connectionist systems depend on the parallel processing of non-symbolic distributed activation patterns. In these systems, contrary of the logical rule-base approach, statistical methods are applied to process information (Medler, 1998). For instance, artificial neural networks (ANN), which are dynamical systems capable of capturing statistical regularities of the training data, are often used (Smolensky, 1996). Learning in ANNs occurs in supervised and unsupervised manner among others. Supervised learning is that in which inputs and outputs are available to the network for example multilayer perceptron (Rumelhart et al., 1986). The task of the network is to predict or adjust inputs to the desired outputs. Unsupervised learning is that in which only inputs are available to the network. The task of the network is to find the correlations among the inputs on its own in order to produce outputs for example Hebbian Learning (Hebb, 1949). Due to the fact that Connectionism is a vast field, it would be beyond the scope of this text to cover it; readers are thus referred to Anderson for further details (Anderson and Rosenfeld, 1988, Medler, 1998).

Varela (Varela et al., 1991) explained that in connectionism symbols play no role and *"the system's connectivity becomes inseparable from its history of transformations, and is moreover related to the kind of task defined for the system"*, meaning that it "*relates to the global state of the system*".

3.1.2.2 Dynamical systems

The cognitive system's mental activities are emergent, situated, historical and embodied. Thus, cognition is not symbolic and representational (Thelen and Smith, 1994). The agent uses self-organization processes to adapt itself to its dynamic environment. The capacity of self-organization comes from the agent's prior experiences. As McClelland (McClelland and Vallabha, 2009) has stated :

"...dynamical systems researchers tend to take more note of the mechanical constraints imposed by the organism's body, while connectionists tend to focus on the constraints among the physical elements within the nervous system (neurons and connections, or at least abstractions of their properties). Likewise, explicitly dynamical models address the constraint satisfaction using dynamical metaphors

such as coupling and stability, while connectionist models address it using neuronal metaphors such as propagation of unit activity and weight change."

McClelland has also stated that some connectionist systems are dynamical systems with temporal properties and structure such as attractors, instabilities and transitions. However, whether or not high-level cognitive processes such as reasoning are possible in dynamic systems remains to be determined. So far, dynamical systems are only used as an analysis tool in cognitive systems (Christensen and Hooker, 2000, Vernon et al., 2007).

3.1.2.3 Enactive systems

Cognition is a history of structural coupling where an entity becomes part of a world or produces a new one. There is no pre-defined information needed and the sensory motor information is processed simultaneously. Thus, to decide the relevance of tasks based on the actual context, an agent needs a real-time interaction with its environment (Varela et al., 1991).

3.1.3 Hybrid systems [9]

Researchers try to combine key aspects of the emergent and cognitivist systems. The representations in hybrid systems are created by the system itself through its interaction with the environment, rather than being pre-programmed (Dreyfus, 1982). Thus, the representation of an object is created through a perception-action process and direct interaction with the object. During the learning phase, there is no direct access to the internal semantic representations of the object in these systems and the system must be embodied (Granlund, 1999).

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[9] Hybrid systems are here considered in this sense and not exactly as the Wooldridge hybrid system.

3.1.4 Conclusion

These aforementioned architectures have their own strengths and weaknesses and have received critics from researchers. For example Christensen and Hooker (Christensen and Hooker, 2000) asserted that enactive and dynamical systems provide us more of a general modeling framework than a model of cognition. They also mentioned that, at present, our knowledge to build artificial cognitive systems based on what emergent researchers have proposed is very limited. Christensen and Hooker have also pointed to three major flaws of the cognitivist systems: the symbol grounding problem (Harnad, 1990), the frame problem (McCarthy and Hayes, 1969), and the combinatorial problem. They have also criticized other problems encountered, such as the limited capacity of cognitivist systems to effectuate generalizations, creativity, and learning. Nonetheless, comparing to the emergent systems, to date, the abilities of cognitivist systems are much superior (Vernon et al., 2007).

As mentioned above, a good alternative to both cognitivist and emergent systems are hybrid systems. However, there is no consensus regarding the manner in which one could combine both cognitivist and emergent systems to create a hybrid system. As Crutchfield (Crutchfield, 1998) argued, dynamics are related to and influence cognition but are *"...not a substitute for information processing and computation in cognitive processes"*. In any case, Crutchfield has recommended that one seek to build design dynamical state structures in such a way that they may support computation (Vernon et al., 2007).

3.2 COGNITIVE ARCHITECTURES

Newell was the first to offer a scheme about cognitive architectures (Anderson, 1983, Newell, 1990, Anderson and Lebiere, 2003). The goal of cognitive architectures is to suggest a unified theory of cognition which encompasses attention, memory, emotion, problem solving, decision making, learning, etc. Furthermore, here, the focus is mostly on the task-independent and homogeneous processes of cognition. Cognitive architectures also specify how cognitive agents are to manage their resources (Langley et al., 2008). Thereby, and in accordance with Vernon's classification, three cognitive architectures such as cognitivist, emergent and hybrid cognitive architectures stand out. According to the cognitive approach, architectures must specify the following components and functionalities: 1) memories, which record knowledge; 2) specific methods and algorithms which are involved in knowledge representation; 3) specific methods and algorithms which manipulate knowledge; 4) learning mechanisms; 5) emotions: because emotions influence our behaviour and thoughts (Purves et al., 2008, Squire and Kandel, 2000, Damasio, 1999), they must be integrated into cognitive architectures. Therefore, like in human, emotions can intervene in different levels and parts of cognitive architectures, for instance in different steps of agents' cognitive cycles (Faghihi et al., 2008a).

The most widely known cognitive architectures include Newell's Soar architecture (Rosenbloom et al., 1993, Laird et al., 1987, Lehman et al., 1998), Anderson's ACT-R architecture (Anderson, 1993, Anderson, 1983, Anderson et al., 2004), Sun's CLARION architecture (Sun, 2006), and Franklin's LIDA architecture (Franklin and Patterson, 2006).

As was mentioned at the onset of this study proposal, the learning mechanisms usually implemented in cognitive agents are loosely connected or are implemented as a collection of learning types in one single mechanism. Furthermore, up to now, no studies have been capable of demonstrating a successful implementation of emotions and emotional learning influencing learning mechanisms in cognitive agents. Thus, we propose and aim to implement an emotional mechanism which collaborates with learning mechanisms in a cognitive agent.

In what follows, in addition to briefly explaining these agents' architectures, we mostly focus on the cognitive architectures' learning problems. We explain very briefly the learning capability of some well known cognitive architectures including Autonomous Agent Robotic (AAR), the Adaptive Control of Though (ACT-R), Connectionist Learning with Adaptive Rule Induction ON-line (CLARION) and Learning Intelligent Distribution Agent (LIDA). Because ACT-R and Soar have much in common, we explain the Soar architecture in the ACT-R section.

3.2.1 Autonomous Agent Robotics

Autonomous agent robotic (AAR), an emergent system, is proposed by Brooks (1986) as an alternative to cognitivist architectures. The fundamental idea behind this architecture is that the robot has no internal representation of the environment and engages completely in interactions with the environment. The whole architecture starts with simple *situation → action* logic and incrementally, layers of more complex tasks are added (*subsumption architecture).* Each layer executes one of the agent's specific goals. The upper layers are more abstract. Decision-making in the upper layers depends on the lower layers. No complex reasoning must be undertaken- it is sufficient to check the rules preconditions to fire them. However, it is the case that this architecture lacks self-management mechanisms and requires a great deal of information about their environment to make decisions, especially when tasks become more complex (Christensen and Hooker, 2000, Wooldridge, 1999). To solve these problems, Brooks identified and integrated the following components to AAR: 1) motivation: action selection is depends on the context; 2) self-adaption: provides a constant adjustment of the system to its sub-systems; 3) development: provides an incremental learning possibility in the system.

The most widely known learning types in emergent systems are associative learning (creating a map between the input-output representations to the system) and competitive learning (Winner takes all) (Wang et al., 2008). However, some researchers such as Hedger (2009) have doubts on whether Brooks' theory is scalable to the level of human beings.

3.2.2 ACT-R's Architecture

The Adaptive Control of Though (ACT-R), developed by Anderson (1983), may be classified as a cognitivist architecture that implements a human cognition model. ACT-R, among others, is one of the validated simulations of human cognition (Anderson and Lebiere, 1998). It uses a modular architecture which consists of a central part with a set of buffers that permit *indirect* communication between different modules within the system.

ACT-R' architecture consists of different modules (Figure 3.1) among which: perceptual (*"visual"*) module for recognizing objects; a goal module whose task is to indicate the system's current goal; a declarative memory module for recovering information from the memory; and a procedural module for controlling agents' movements (or actions, in general). In this architecture, modules cannot communicate directly: any communication must pass through the *"central production system".* Each buffer contains one *declarative* piece of knowledge, called a "*chunk*". Such a "*chunk*" consists of a name and has labelled links towards other "*chunks*". Together, these form a "*semantic network*". The inference module modifies the content of buffers following a set of rules called *"productions".* Each *production rule* is composed of conditions (which indicate to which configuration, or content of the buffers it is applicable) and actions (indicates how it modifies the buffers). ACT-R uses the production rules to solve procedural problems (for example a mathematical subtraction). These rules are specific to the application, but ACT-R provides meta-rules to choose and execute a particular rule, because in each cycle the system is capable of executing one rule. Cognitive cycles in ACT-R start by finding a pattern for external or internal images of the world which correspond to the buffers; then, a production rule is triggered, and buffers are updated for the following cognitive cycle. This complete cycle takes about 50ms.

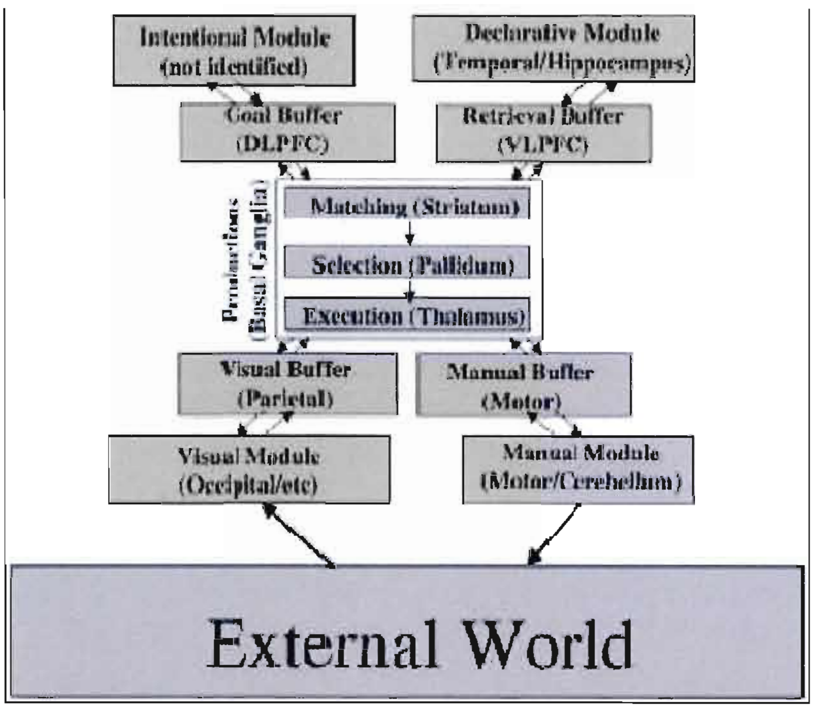

Figure 3.1 ACT-R 5.0's Architecture

Learning in ACT-R occurs at the symbolic and sub-symbolic level within an integrated learning mechanism; this, for both *chunks* and *production* rules. Explicit learning in ACT-R is the result of learning the content of declarative memory when fetched and examined. It also occurs at the procedural level through the combination of two rules.

Implicit learning occurs for both declarative and procedural knowledge. In declarative knowledge, there is an increase or decrease of the activation of chunks. When a chunk is learned, its *base-level* energy is stored into declarative memory. Later, each time the chunk is recalled, its base-level activation increases and the strength of association between the current sources and the chunk also increases. This will increase its probability of being recalled. To determine if a chunk will be recalled following a procedure execution, the activation will be calculated by considering various information such as the base level activation, time elapsed since the last recalls, the context, noise, etc; In procedural knowledge, each time a procedure is used while executing a task, it is updated with success or failure information (each experience can both increase/decrease the rule strength and its probability of being fired in the future).

However, in ACT-R, the rules for all situations must be specified in advance. ACT-R *episodic memory* does not address a role for emotions in the episodic learning, and causal learning (Faghihi et al., 2009a, Faghihi et al., 2010). ACT-R is unable to explain the *bottom-up learning* of the explicit knowledge and the interaction between explicit and implicit knowledge (Hélie, 2007). Like ACT-R, Soar architecture is a production system (Rosenbloom et al., 1993, Laird et al., 1987, Lehman et al., 1998). Soar has a Working Memory (WM), Long-Term Memory (LTM), and a goal stack. The WM in Soar detects external stimuli to the system and tries to find and fetch relevant production rules from system' LTM. Once rules fetched into the system's WM, their utility are verified upon to the current goal stored in the system's goal stack and then the best rule is chosen and fired. Like ACT-R, Soar uses chunk to automatize utilization of the rules. The Soar architecture can only learn new production rules (Nason and Laird, 2005).

3.2.3 CLARION's Architecture

In order to obtain various cognitive processes within a single cognitive architecture, Sun created the *Connectionist Learning with Adaptive Rule Induction ON-line* (CLARION) architecture (Sun, 2001, Sun, 2006). CLARION is a hybrid system and a cognitive modules-based agent. In this cognitive architecture explicit (declarative) /implicit (non-declarative) knowledge's interact in a synergetic way to solve a problem and to learn a specific task. The explicit knowledge is accessible by the agent consciousness system whereas the implicit knowledge is not accessible (or difficult to access) by consciousness when system performs a task. The interactions between implicit and explicit knowledge levels are realized by the integration of *connectionist*, *reinforcement*, and *symbolic* methods to obtain several learning abilities, such as bottom-up learning, trial-and-error learning, and top-down learning.

CLARION is equipped with a procedural memory, a declarative memory and an episodic memory. The most important challenge in CLARION' architecture is the interactions between implicit and explicit knowledge that the agent acquires from its environment. To separate implicit knowledge from explicit knowledge, Sun suggested a distributed system with sub-systems. Each sub-system has two levels- the top level encodes explicit knowledge and the bottom level encodes implicit knowledge.

In Figure 3.2, ACS (the "action-centered sub-system") controls internal and external actions decision making. NACS ("*non-action-centered subsystem*") role is to store up the explicit, implicit and episodic knowledge and performs as the reasoners of the system. MS is the motivational subsystem for feedback purposes. MCS ("*meta-cognitive subsystem*") observes ACS and all other sub-systems of the agent, their activities and operations in order to change them when needed (for example, when new feedback is received)(Sun, 2006, Hélie and Sun, 2008). The agent explores its environment and tries to acquire information or modify it (for example, hypothesis testing without the help of bottom level). The action selection mechanism in CLARION is formed by different top/bottom levels. There exist input and output for both levels. A state entered from the environment into the system will be analyzed at first, and then an appropriate action will be allocated, according to the system goal. The feedback will be learned and saved for future uses. In fact, the feedback could be translated into "*rules*" and "*chunk*" in the explicit knowledge level. Furthermore, some existing nodes in the bottom level may be relevant to the condition of a sole node at the top level. Thus, each action took by the bottom level will produce a node with some related rules in the top level after extraction of explicit rule and then it will be refined by future interactions with external world. Learning in CLARION is accomplished by the integration of reinforcement learning and rule induction, so that the resulting process is integrated automatically in the structure. Implicit learning occurs in the bottom level with supervised learning ("*back-propagation network*") by input/output parameters adjustment.

Explicit learning occurs by extracting acquired knowledge from implicit knowledge into symbolic representations. In fact, explicit knowledge is an extraction and refinement of information that was captured from interaction with environment (implicit knowledge). Conversely, explicit knowledge will be integrated into the bottom level after it becomes stable (Hélie and Sun, 2008, Sun, 2006, Sun, 2001).

However, in CLARION current version, during bottom-up learning, the propositions (premises and actions) are already present in top level (explicit) modules before the learning process starts, and only the links between these nodes emerges from the implicit level (rules). Thus, there is no unsupervised causal learning for the new rules created in CLARION (Hélie, 2007). The second problem in CLARION is that although emotions were originally designed in the system, it is not clear how they influence different cognitive process such as Episodic Learning.

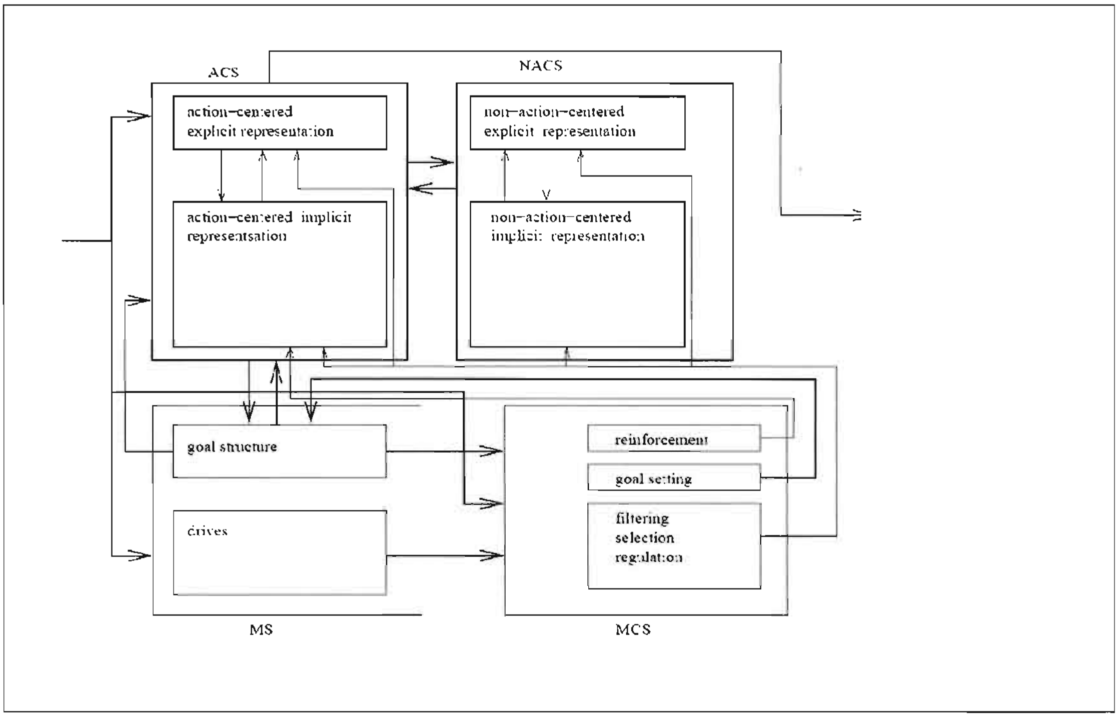

Figure 3.2 CLARION's Architecture

3.2.4 LIDA's Architecture

Learning Intelligent Distribution Agent (LIDA) (Figure 3.3) is a hybrid cognitive architecture, developed by Stan Franklin and his colleagues at the University of Memphis (Franklin and Patterson, 2006). LIDA is IDA's successor; IDA was originally conceived to assign new billets to sailors. In the American Navy, at the end of each sailor's tour of duty, he/she is assigned a new billet (task) by a detailer. IDA performs the detailer's role. It communicates with sailors via e-mail and must understand sailors' requirements and preferences, as well as respect all constraints of the Navy. To reply to the sailors, it has to communicate with different databases (Franklin et al., 2005, Franklin and Patterson, 2006).

LIDA's architecture is partly symbolic and partly connectionist and is equipped with six artificial intelligence software technologies: a copycat architecture, a sparse distributed memory, a global workspace, a schema mechanism, a behaviour net, and a sub-sumption architecture.

Franklin called LIDA a "conscious agent" for its fundamental elements and processes rely on functional consciousness as described by Baars (Baars, 1997). LIDA is constructed with simple agents called "codelets" (which reproduce Baars' "simple processors"). The central point of the system is the "access consciousness", which allows all resources to access centrally selected information that is "broadcast" to unconscious processes (which guides the agent to be stimulated only with the most relevant information).

LIDA's main components are the following:

1) Perceptual Associative Memory: This corresponds to the different sensorial cortices in human (visual, auditory and somatosensory). In LIDA, perceptual nodes are situated in a slipnet. This allows the agent to distinguish, classify and identify external and internal information. There are activations and connections between slipnets' nodes. Segments of the slipnet are copied into the agent's working workspace (D'Mello et al., 2006);

2) Workspace: This corresponds to the human preconscious buffers of working memory. This is the "place" that holds active *codelets and the strength between them*, which come from perception. It also includes previous percepts not yet decayed away, recalls from long-term memories. Information written in the workspace may reappear in different cognitive cycles.

3) Episodic memories: These are the memories for events (what, where and when) and is divided into transient episodic memory, and a long-term *autobiographical* episodic memory;

4) Functional Consciousness: This is the functional implementation of the Global Workspace (GW) theory suggested by Baars (Baars, 1997). Its main elements are codelets which run autonomously and are meant to perform one specific task. Functional consciousness' main components are the coalition manager, the spotlight controller, the broadcast manager, and the attention codelets that identify important events or urgent situations;

5) Procedural Memory: LIDA's procedural memory deals with deciding what to do next. It is similar to Drescher's schema mechanism but with fewer parameters (Drescher, 1991, Drescher, 1988). The scheme net is a directed graph in which each of the nodes has a context, an action, results and links towards others nodes. To instantiate and fire a scheme, LIDA uses Maes' Action Selection mechanism (Maes, 1989), in its Behaviour Network with some modifications (Negatu and Franklin, 2002).

Thus, in LIDA's architecture, while procedural memory is responsible for deciding what will be done next, sensory motor memory is responsible for deciding how tasks will be performed. Thus, each memory requires a distinct mechanism.

LIDA performs through its cognitive cycles (Figure 3.3) which occurs five to ten times a second. A cognitive cycle starts by a perception and usually ends with an action. It is conceived as an iterative, cyclical, active process that allows interactions between the different components of the architecture.

In what follows, we briefly explain LIDA's cognitive steps, which are taken from Franklin and his colleagues' papers(D'Mello et al., 2006).

1) **Perception**: The process of ascribing the meaning of incoming sensory data.
2) **Percept to preconscious buffer**: All interpreted data and meaning is stored in LIDA's Working Memory's preconscious buffers, adding to pre-existing information which has not yet decayed away.
3) **Local associations**: Information associated with the cues are retrieved automatically from different memories such as transient episodic memory and declarative memory, and stored back in Long-term Working Memory.
4) **Competition for consciousness**: Here, attention codelets (AC) observe Long-term working memory content and try to distinguish important events or urgent situations in order to form coalitions describing them and bringing them to consciousness.
5) **Conscious broadcast**: This refers to a coalition of codelets that is chosen by Attention and brought to consciousness. It is broadcast to all modules.
6) **Recruitment of resources**: The most relevant schemes respond to the broadcasted information.
7) **Setting goal context hierarchy**: in this step, a scheme is selected in response to the broadcast to instantiate a new goal in the behaviour net.
8) **Action chosen**: LIDA's Behaviour Network manager selects a behaviour from current or previously instantiated behaviour streams according to the presence of preconditions and based on the most activated scheme.
9) **Action taken**: The selected behaviour is executed. Each action codelet spawns at least one expectation codelet to monitor and bring back the results of the act to consciousness for future decision-making.

In LIDA, learning occurs through consciousness (D'Mello et al., 2006). Different types of learning have been implemented in LIDA: 1) **perceptual learning** (e.g., learning of new objects): it is implemented as a semantic net (slipnet). It occurs by the creation of new nodes or strengthening or weakening of the base-level activation of the existing nodes in the slipnet after the consciousness mechanism broadcasts information; 2) **episodic learning**: it occurs each time the agent finds an episode in the content of consciousness; it, then, connects the source of activation in the current episode in the *Slipnet* to the basic features sensing elements. This information about the event will be encoded in LIDA's transient episodic memory. The recall of the saved event occurs by finding the corresponding perceptual symbols through slipnet nodes; 3) **Procedural Learning**: this refers to the learning of new actions and action sequences, and is implemented through LIDA's *Scheme Net* as a combination of *instructionalist* and *selectionist concepts.* Nodes (actions) are either created, strengthened, or weakened at the base-level activation of the existing nodes in the *Scheme Net* after consciousness broadcast the information in the system (D'Mello et al., 2006).

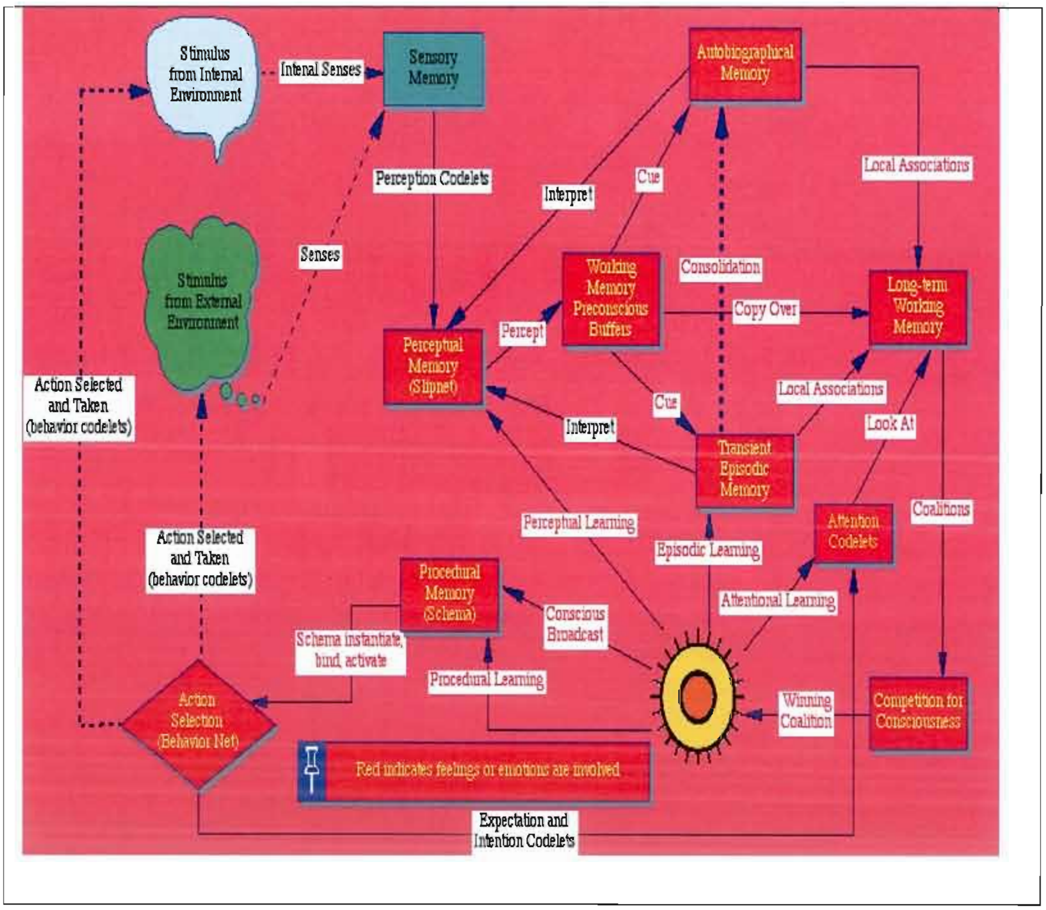

Figure 3.3 LIDA's cognitive cycle (Franklin,S., 2006)

However, although causal learning was initially designed for LIDA's architecture, it has never been implemented. In LIDA's procedural learning, D'Mello (D'Mello et al., 2006), has proposed that the result of each action must be brought back to consciousness, whereas experiments relating to implicit learning demonstrate that satisfied expectations usually do not provide feedback to the subject (Cleeremans, 1997, Cleeremans and Jiménez, 1996, Cleeremans and Jiménez, 2002, Curran and Keele, 1993). Finally, for episodic learning, in the recall phase of an event, LIDA finds corresponding nodes in its slipnet. However, no similar method has been proposed for procedural learning, though we, as human being, have reflexes. For instance, we have reflexes for certain types of perceptual stimuli (Squire and Kandel, 2000).

3.2.5 Conscious Tutoring System' (CTS) Architecture

In this part, we briefly explain CELTS' original architecture (Figure 3.4), without its newly added emotions and learning capacities. These will be covered in the next chapters. Based on IDA's (and LIDA's, its evolution) (Franklin and Patterson, 2006), CTS' conceptual architecture is partly symbolic, partly connectionist. CTS was conceived based on both cognitive and engineering concepts. CTS respected cognitive concepts by implementing Baars(1997) global theories, detailing how the human mind works (see Dubois,2007 for more details). CTS also abides engineering concepts in its solution to the design and implementation of software information agents and cognitive robots, promising better learning mechanisms and more human-like intelligence.

CTS is a distributed and modular architecture which relies on the functional "*consciousness*" mechanism for much of its operation. Its modules communicate with one another (though rarely) and contribute information to Working Memory (WM) through information codelets. These travel back and forth through cycles of "conscious publications" that broadcast only the most important, urgent, or relevant information.

Although CTS' general design is very similar to IDA's, there are some differences in CTS' memory structures and functionalities (see Figure 3.4). For more details, the reader is referred to Dubois' thesis (Dubois, 2007).

CTS' main constituents are codelets (of many types and roles), "consciousness"[10] mechanism, perceptual, semantic memories, and Behaviour Network (BN). Its cognitive cycle incorporates the traditional Perception-Reasoning-Action phases, but in a more detailed manner (quite close to IDA's).

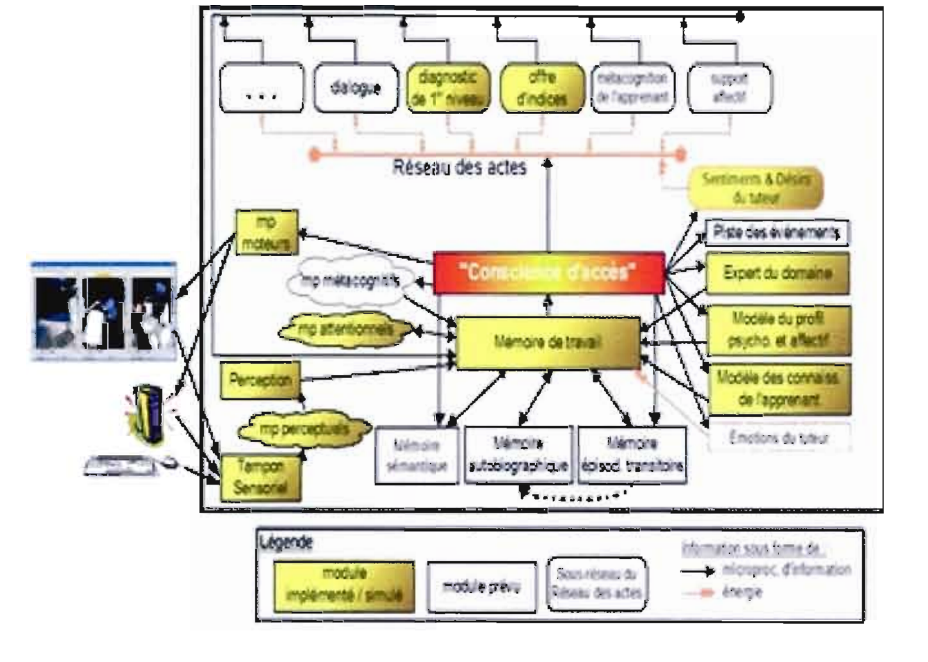

Figure 3.4 CTS' Architecture without Emotion and Learning (Dubois, 2007)

Cognitive cycles begin when external stimuli are interpreted by CTS' perceptual mechanism and written into WM, where they may then be chosen by the attention mechanism to be presented to consciousness. That broadcast information may either assert preconditions for the initiation of behaviour in BN, or it may cause reactions from another part of the system, which then creates the necessary

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[10] *Consciousness: Conscious cognition is implemented computationally by way of a broadcast of contents from a "global workspace", which receives input from the senses and from memory (Franklin & Patterson.2006).*

preconditions for firing a behaviour. When one type of behaviour is chosen in the BN, it activates the codelets that implemented it.

CTS' BN (Figure 3.5) implemented based on Maes' Behaviour Net (Maes, 1989). It is a high-level procedural memory. It is a network of partial plans that analyse the context to decide what to do and which type of behaviour to set off. This structure is linked to the latent knowledge of how to do things in the form of inactive codelets. Each behaviour node (Figure 3.5.A and B) may contain messages, questions, propositions, etc. (Figure 3.5.C) and CTS uses them to communicate with users (Figure 3.5.D). Just like codelets, they, have a base-level activation, which can increase or decrease (Figure 3.5.A). Until it is selected for execution, a behaviour node accumulates energy from the various sources in the BN (feelings, state nodes, other nodes), but they are at the same time submitted to a constant loss of activation. Links between the nodes require energy (Figure 3.5.B); learning is linearly related to energy, and nodes weaken when not used (when the nodes they link are not selected for execution). This mimics human beings: if we do not repeat a task for a while, we will lose some of our ability, forgetting with the passage of time (Faghihi et al., 2007).

CTS' original cognitive cycle proceeds in eight steps:

Step 1: CTS perceives its environment (object recognition).

The first stage of the cognitive cycle is to perceive the environment; that is, to recognize and interpret the stimulus.

Step 2: The percept enters WM:

The percept, which is constituted by the active semantic nodes of the Perceptual Network (PN), enters Working Memory (WM) as a single network of codelets.

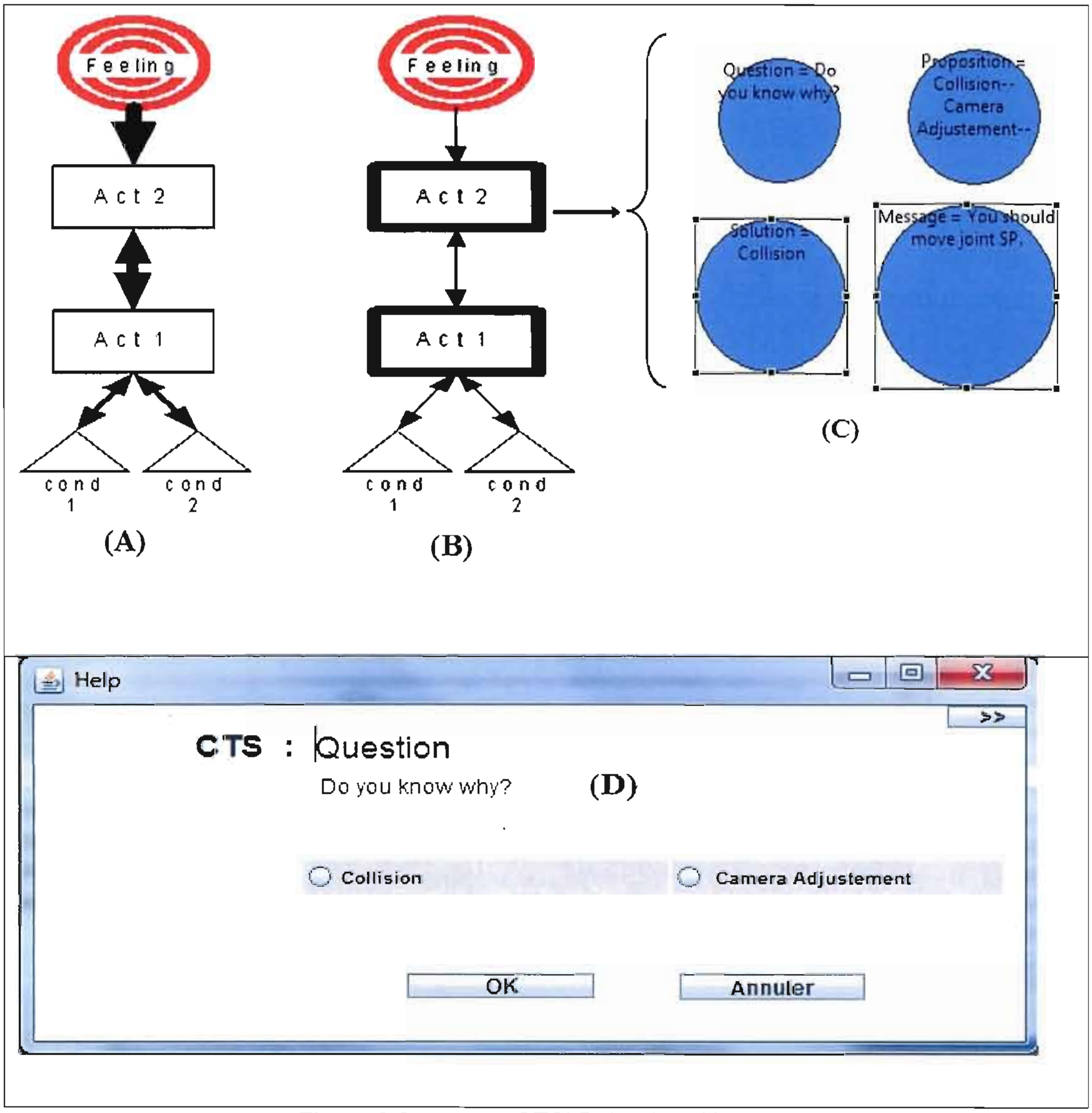

Figure 3.5 CTS' Behaviour Network

Step 3: Memories are probed and other unconscious resources contribute[11]:

All these resources react to the last few consciousness broadcasts (internal processing may take more than one single cognitive cycle).

Step 4: Coalitions assemble:

[11] Step 3 to 5 could be viewed as a representation of blackboard (for whom is familiar with this architecture) with more details.

In the reasoning phase, coalitions[12] of information codelets are formed or enriched. Attention codelets join specific coalitions and help them compete with other coalitions toward entering "consciousness".

Step 5: The selected coalition is broadcast:

The Attention mechanism (AM) spots the most energetic coalition in WM and submits it to "access consciousness" which broadcasts it to the whole system. With this broadcast, any subsystem (appropriate module or team of codelets) that recognizes the information may react to it.

Steps 6 and 7: Unconscious behavioural resources (action selection) are recruited:

Step 6, among the modules that react to broadcasts is the Behaviour Network (BN) (Maes, 1989, Tyrrell, 1994)(Figure 3.5.A,B,C). BN plans actions and, by an emergent selection process, decides upon the most appropriate act to adopt. (Step 7) The selected behaviour then sends the behaviour codelets linked to it.

Step 8: Action execution:

Motor codelets stimulate the appropriate nodes (effectors or internal processes).

CTS is a generic architecture applicable for different purposes. However, in our case it is used to assist astronauts in learning how to manipulate Canadarm2 (Figure 3.6). The international space station (ISS) has been designed and implemented to accommodate scientific experiments and life in the space. Thus, it needs to be supplied constantly with foods, fuel, inspections, etc. Canadarm2, a mobile and robotic arm installed on the ISS permits astronauts to move the arm from one configuration to another. For instance, astronauts may use Canadarm2 to charge or discharge the received food from the space shuttles. Thus, manipulating the robotic arm is a difficult task, which requires astronauts to undergo a serious amount of training. The seven degrees of freedom of the arm is the first difficulty to overcome, as it considerably increases the number of possible operations. The second difficulty is sight limitation. It is impossible to have an overall view of the station; therefore, the

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[12] For example, a coalition could describe Canadarm2 nearing collision with the virtual world

astronaut can only see the arm through a "steady climb" camera installed on the station and on the Canadarm2. Furthermore, the astronaut must choose among these cameras because there are only three screens.

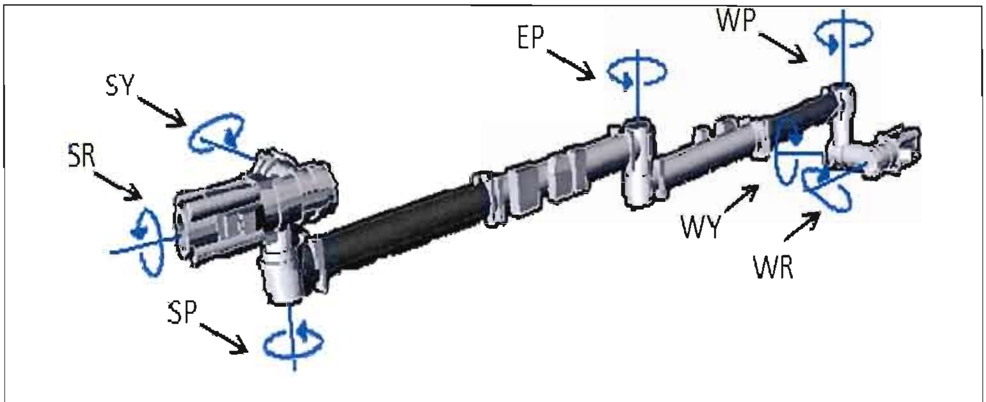

Figure 3.6 Robotic arm installed on the International Space Station[13]

Figure 3.7.A, shows an astronaut manipulating Canadarm2 and the three screens of Canadarm's workstation aboard the ISS.

Thus, during Canadarm2 manipulation, astronauts must avoid moving it in a way that might block it or produce a collision with ISS. Beyond the main task of manipulation comes selecting the right cameras. In addition to choosing the best views, the astronaut must continuously readjust the cameras while moving Canadarm2 from one configuration to another. Our laboratory, in co-operation with the Canadian space agency, developed an Intelligent Training Robotic Simulator which uses an Innovative Path-Planner (Nkambou et al., 2006). It is called CanadarmTutor (Figure 3.7.B).

[13] Source : http://www.nasa.gov/mission_pages/station/structure/elements/mss.html

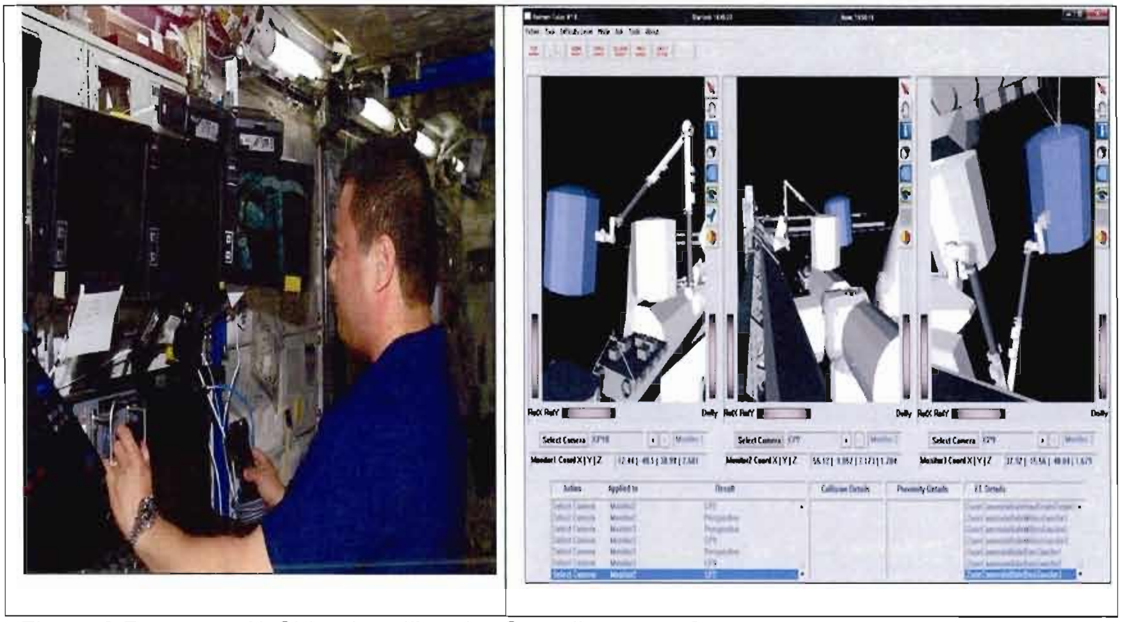

Figure 3.7 A) Chiao handling the Canadian Arm (Courtesy of NASA); B) The CanadarmTutor user interface (Nkambou et al., 2006)

It assists astronauts in self-learning without human supervision. *CanadarmTutor* is capable of indicating the distance between Canadarm2 and ISS, dangerous zones, obstacles, etc., to astronauts. It also makes it possible for the user to test Canadarm2 in a virtual world and to complete exercises assigned by the tutor. It is also capable of finding a path from a given situation permitting to move Canadarm2 to the assigned destination. Astronauts are therefore provided with various contexts in which they can manipulate Canadarm2 (Figure 3.7.B). CTS was integrated to *CanadarmTutor* to allow it to more efficiently analyze astronauts' behaviour. For instance, it is now capable of finding the cause of astronauts' problems, adapting to them, proposing better dialogue for communications, etc (Dubois, 2007). Thus, the learners' manipulations of the virtual world simulator, simulating Canadarm2, constitute the interactions between them and CTS. In particular, the virtual world simulator sends all manipulation data to CTS, which, in turn, sends learners advice to improve their performance. To do this, CTS uses the three panes of a consciousness viewer (Figure 4.5) Figure 3.8 : 1) Last Message: Perceptual information received from the simulator; 2) Current Scene: Working Memory (or scene,as in Baars' metaphor) in which all interpreted data from the simulator and from other sources are temporarily written; 3) Broadcasted: All relevant information (codelets) brought into Consciousness and broadcasted to all entities in the system;

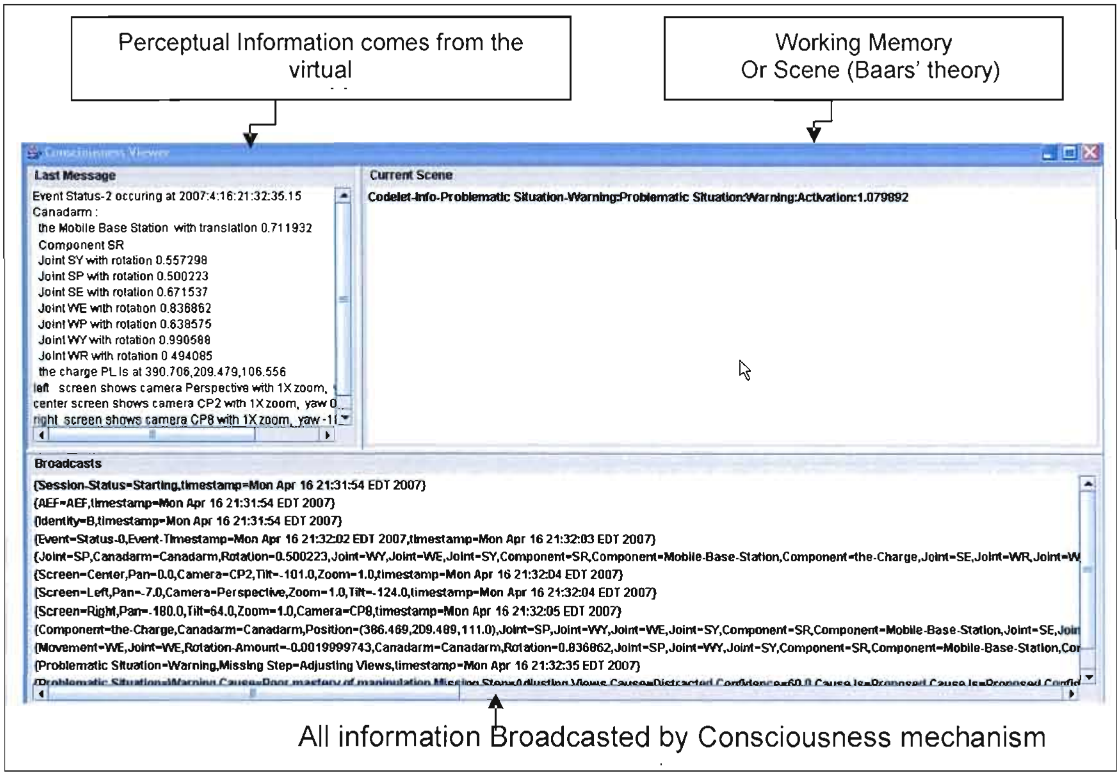

Figure 3.8 CTS' consciousness viewer

CTS' original architecture was not equipped with emotions and learning mechanisms. Some learning mechanisms such as learning of environmental regularities (both implicit and explicit) and implicit procedural learning have been implemented by Faghihi (2007) in CTS. In this study, we propose CELTS, the new version of CTS, by explaining how emotions and three types of learning mechanisms (emotional learning, episodic learning and causal learning) can be integrated into it.

3.2.6 Comparison between different Architectures' learning capabilities

At this point, we compare CTS' learning capabilities (its version of 2007) with three popular architectures explained briefly in this chapter. The comparison ignores the Emotion, Episodic and Causal learning mechanisms proposed and implemented in this study. CTS' architecture is unlike to ACT-R's architecture as it is not a unified theory of cognition as postulated by Newell (Newell, 1990). Its modules are implemented in a distributed manner by means of different mechanisms such as pandemonium theory, behaviour network. While CTS' integrates a symbolic and connectionist approaches, ACT-R integrates production rules.

In CTS, unconscious codelets perform similar to the bottom-level of CLARION; and global workspace could be considered as its top-level module which "synthesizes" bottom-level modules. CLARION is not as useful as Baars as far as internal uniformity is concerned, but its architecture has partial functionality in the emersion of consciousness.

CTS' architecture permits learning in both an explicit and implicit fashion. Both explicit and implicit procedural learning are implemented in the architecture. As opposed to LIDA, no episodic and perceptual learning were implemented in CTS' 2007 version. However, while implicit procedural learning is implemented in CTS, it is not implemented in LIDA's architecture (Faghihi et al., 2007).

CTS' explicit learning is similar to ACT-R's in which codelets are learned when they are fetched for the first time from declarative memory. However, there is no codelets combination in CTS' BN, as for explicit learning, for the rules in ACT-R. CTS' implicit learning of declarative memory content is similar to ACT-R in which codelets' base-level energies increase or decreases when they call to WM and spend time together. Implicit learning of procedural learning in CTS is also similar to ACT-R's in which for a given problem, after each execution, the behaviour receives success or failure and positive or negative energies, thus making their probability of being fired in the future increase or decrease. Implicit learning in CTS' BN occurs for the behaviour's base-level energies and the links among them (Figure 3.5) (Faghihi et al., 2007).

CLARION's explicit learning mechanism is similar to CTS's in which it learns symbolic representation- codelets in CTS and meaningful symbols in CLARION. CLARION' reinforcement learning is similar to CTS's implicit learning in which BN's behaviour, after each execution, receives success or failure and positive or negative energies. However, CTS is not equipped with the supervised learning implemented in the CLARION' bottom-level in which it uses back-propagation algorithms to capture implicit knowledge (Sun and zhang, 2004).

It is worth noting that while ACT-R is not capable of bottom-up learning for explicit knowledge, this learning is implemented in a supervised fashion in CLARION (Sun and zhang, 2004, Hélie, 2007). Bottom-up learning is implemented for all three types of learning such as episodic, perceptual and procedural in LIDA' architecture (Duch et al., 2008). CTS' procedural learning and the learning of regularities are also implemented as bottom-up learning (Faghihi et al., 2007).

	LIDA (Franklin, 2006)	ACT-R (Anderson, 1983)	CLARION (Sun, 2006)	CTS (Dubois, 2006)
Explicit Perceptual Learning	X	—	X	—
Episodic Learning	X	X	—	—
Explicit Procedural Learning	X	X	X	X
Implicit Procedural Learning	—	X	X	X
Emotional Learning	—	—	—	—
Bottom-up Supervised Learning	X	—	X	—
Supervised Causal Learning	—	X		—

Table 3.1 Comparison between LIDA, ACT-R, CLARION and CTS (— =the architecture is not equipped with this specific learning; X = the learning mechanism is implemented)

3.3 COGNITIVE ARCHITECTURES AND EMOTIONAL MODELS

Due to the important role emotions play in cognition, cognitive modellers have sought to include emotional mechanisms in their agents' cognitive architecture.

However, while psychological theories propose an abstract approach to the study of emotions, the computational models propose a pragmatic framework to it. Thus, the implementation of emotions in a computational fashion impacts psychological theories by revealing their limits and hidden hypotheses (Steunebrink et al., 2009, Marsella et al., In press).

Various models have been proposed up to now. While some computer scientists are interested in using emotion to make their agents more believable, others work on the functional aspects of emotions and their influences on the agents' behaviour, learning and social aspects (Adam, 2007). The first group is not covered in this study. For more details, readers are addressed to Adam' thesis (Adam, 2007). The second group implement an Emotional mechanism in their agent using a '*Centralists*' approach such as Gratch and Marsella (2004), Velásquez (Velásquez, 1996, Velásquez, 1997) and Franklin (2006). They are very briefly explained in what follows.

1) **Gratch and Marsella's model:** Gratch and Marsella (2004) proposed Emotion and Adaptation (EMA), a plan-based computational model of emotion based on the appraisal theory of Lazarus (Lazarus, 1991). Plans are built according to their probability or utilities. Causal interpretation is the key concept in EMA' architecture to find the causal relationship between agent emotional states and corresponding events to judge their relevance given the agent's goal. Three important elements in causal interpretation are the past causal history, the actual situation of the environment and agent, and the future. The appraisal process task is to map causal interpretations to appraisal variables which cause one or more emotions to be set off by the system. From fired emotions, the most intense will permit coping processes to find a remedy to the current problem. EMA is equipped with different coping strategies such as denial, shift blame, acceptance, etc. To be capable of predicting the outcome of executed actions and making appropriate causal relationships, the authors put stress on the explicit representation of the agents' intention and belief. Thus, a

coping strategy may influence causal interpretation by altering EMA's current intention, utility or probability values (Mao and Gratch, 2006, Marsella et al., In press, Adam, 2007).

Although researchers in psychology postulate the direct link between appraisal and coping, it is ignored in this model (Adam, 2007). The model does not integrate cognitive neuroscience evidence for the short and long routes of emotion, as explained by LeDoux and Cannon (LeDoux, 2000, Cannon, 1927). In fact, all human behaviour is not the production of causal interpretation processes (reflexes are good exceptions). The second problem is that the model uses probability approaches to find relationship between different components of the model. Probability approaches are accompanied by the risk of combinatory explosion in the case of huge amounts of data. The model also turns out to be too expensive to apply to large populations of real-time agents such as combatant agent (Parunak et al., 2006).

2) **Velásquez's emotional model** (Velásquez, 1996, Velásquez, 1997)**:** the Cathexis architecture describes and integrates psychological and biological aspects of human's emotions in detail. Proto-specialists (subagents) control the six basic emotions such as anger, fear, distress/sadness, enjoyment/happiness, disgust and surprise. Each emotion has an activation threshold, saturation (maximal value for emotion) and a decay function (duration of emotion). Proto-specialists perform in parallel and continuously update their parameters. According to the current situation and/or previous emotional states, proto-specialists may set off a particular emotion or may send inhibitory or excitatory energy toward others. The temperament of the agent is decided upon the emotion's activation and saturation values. Moods are distinguished by being more resilient and having lower activation comparing to emotions. In this architecture, internal and external sensors and proto-specialists can alter agent's emotional states. Changes in the agent's emotional states occurs in both cognitive

and non-cognitive fashion such as cognitive (e.g. appraisal), motivations (e.g. hunger), sensory motor stimuli (e.g. body posture), and neural activities (e.g. neurotransmitters). The expression of behaviour occurs by action selection. This occurs by choosing the most energetic behaviour through a network of behaviours that are in competition. Generally, the model attempts to simulate the real process of emotions as defined in humans. Finally, the model proposes only a simple model of behaviour.

However, there is no standard measurement proposed by authors to decide how precise the proposed model is comparing to human's emotional activities. In addition, the model ignores explanations of how the emotional memory influences learning and behaviour in the architecture. For instance, for a given situation, how do emotions influence the consolidation and remembering phase of episodic memory?

LIDA (Franklin and Ramamurthy, 2006): Franklin, in his cognitive agent, also attempted to design emotions. The influence of emotions in LIDA's architecture can be seen in different part of the system and through its cognitive cycles, but the *consciousness* mechanism is the necessary intermediate in all of these interventions. Emotions intervene endlessly through the loop of perception-deliberation-action selection. However, the paper does not detail how emotions help different types of learning in the agent. Furthermore, LIDA's architecture ignores the implicit emotional reactions in its cognitive cycles, which are documented in both neurobiology and psychology studies of the human brain (Squire and Kandel, 2000, Purves et al., 2008).

3.3.1 Conclusion

Until now the means of implement of emotions in cognitive agents have made peripheral–central learning impossible (James, 1884, Cannon, 1927). To best resemble humans, cognitive agents' emotions should be capable of influencing the different types of learning and decision-making. However, as it was mentioned previously, various types of learning are functionally incompatible (Sherry and Schacter, 1987). Thus, in order to implement emotions and learning mechanisms in cognitive agents, one important task is to define how they collaborate with each other. The collaboration between these mechanisms must be defined as a set of complementary rules. Furthermore, we suggest that emotions and learning mechanisms should be implemented in a modular and distributed fashion. Although ACT-R, CLARION and LIDA used the concept of emotions in their architectures, none proved capable of improving learning mechanisms. However, in some of them, emotions do influence decision-making. Our proposed model, conversely, allows for both the peripheral–central and the Centralists model to produce emotional reactions and learning. In the following chapter, we propose the implementation of an emotional mechanism for cognitive architectures. In our model, emotions not only influence different types of learning, decision-making and behaviour in CELTS, but also permit that agents be brought to a self-satisfaction state.

CHAPTER IV

IMPLEMENTATION OF EMOTIONS AND EMOTIONAL LEARNING MECHANISMS IN CELTS

In this chapter, we explain how to best insert an Emotional Mechanism (EM), and Emotional learning in an artificial agent's cognitive architecture, based on evidence from cognitive neuroscience and with respect to the several theories of emotions presented in Chapter II. We also detail how EM influences different modules in CELTS, implicitly or explicitly. The influence of EM in Episodic and Causal learning will be detailed in the next chapters. It is worth noting that, so far, no specific feature has been found that could allow cognitive architectures to have something similar to human feelings. Thus, our discussion of the implementation of emotions in cognitive architectures covers only emotions in their functional context. It must also be noted that the emotions of cognitive agents need not all be similar to those of humans. Our work on emotion is based on the OCC model and the work of Ledoux (LeDoux, 2000) on fear conditioning and the amygdala, which extends current models by defining emotional learning as a parameter that helps different types learning (e.g. Episodic Learning) and helps differentiating a variety of emotions. Emotional learning is here taken to be CELTS' memorization of valenced[14] reactions to given emotional situations (stimuli) as described in the OCC model (Ortony et al., 1988).

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[14] Emotional valences are between -1 and +1

4.1 CELTS' Emotional Architecture

In this section, we propose our generic computational model of emotion which explains in details how the "peripheral-central" (LeDoux, 2000, Cannon, 1927) model is implemented in CELTS. As explained by Phelps (2006), emotions influence attention, and vice-versa. Accordingly, in CELTS' cognitive cycles, when the percept enters WM as a single network of codelets, the emotional codelets inspect each coalition's informational content, and infuse it with a level of activation proportional to its emotional valence. This increases the likeliness that some coalition draws attention (AM) to itself. This emotional intervention on the coalitions in WM is how CELTS' Emotional Mechanism (EM) (which we call "pseudo-amygdala") gets involved in CELTS' long route (ELR rectangles in Figure 4.1). Attention influences the EM by providing information about the environment regarding the discrepancy between what was expected and what effectively occurred. This may alter the future valence assigned by EM to situations in the environment, as well as the importance EM gives to a situation. In our model, after each interaction with the environment, CELTS' EM updates its information (especially in dangerous situations) about its surrounding environment for future situations. Thus, the importance of any given situation may increase or decrease in CELTS' next encounters with it.

Before explaining our model in detail, we first explain the typical situation experienced by astronauts, in a virtual world. For instance, when an astronaut manipulates Canadarm2 in the virtual world, information coming from the simulator may describe an imminent collision. A collision is very dangerous on the ISS and the tutor must immobilize the arm. Once it has done so, CELTS interprets more attentively the information received from the virtual world. It must recognize which movements will not cause collisions. CELTS then gives feedback to the user such as a hint. The first reaction taken by CELTS will then be adjusted for future interactions with any astronaut.

CELTS can make two reactions when faced with a dangerous situation. We now explain how the information, coming from CELTS' perceptual Mechanism, flows along the short and long route (ESR and ELR in Figure 4.1).

The first step here is the Short route. The short route (see ESR rectangles in Figure 4.1) starts with perception just like the long route (see ELR rectangles in Figure 4.1). The perception codelets connect in parallel both to CELTS' Behaviour Network (BN) and to its emotional codelets. The activation sent directly by perception codelets to emotional codelets is the first stage of the short route. The Emotional Mechanism (EM) establishes the positive or negative emotional valance of the event for the system. The valence assigned to the event may result from evolution (an innate valence accorded to evolutionarily important situations) or from learning.

Thus in CELTS, some emotional codelets might correspond to innate (designed) sensitivities (e.g., to excessive speed for Canadarm2, or to an imminent collision); other emotional codelets may have learnt the valence of situations from experience. Either way, emotional codelets possess direct connections to behaviour nodes in the BN, to which they send positive or negative activations. Some of these emotional codelets react more strongly than others and so send out stronger valence activations to the behaviour nodes. If the valence activations exceed a behaviour node's firing threshold, then the corresponding action will fire automatically. This emotional intervention reflects a direct route between the amygdala and bodily responses, influencing action selection. This corresponds to James' theory (James, 1884) that explains why a bodily reaction generates an emotional feeling, if an important stimulus directly causes the bodily reaction.

Whichever route was responsible, short or long, the firing of a behaviour node generates one or more Expectation codelets, which are a type of Attention codelets in CELTS. These codelets are processes that watch for the arrival in WM of a given piece of information, expecting to see, within a given time frame, some specific result(s) for the action taken by CELTS. The expectation codelets have a double duty in CELTS. First, they serve as "environmental reinforcers" to the Action Selection Mechanism in the BN.

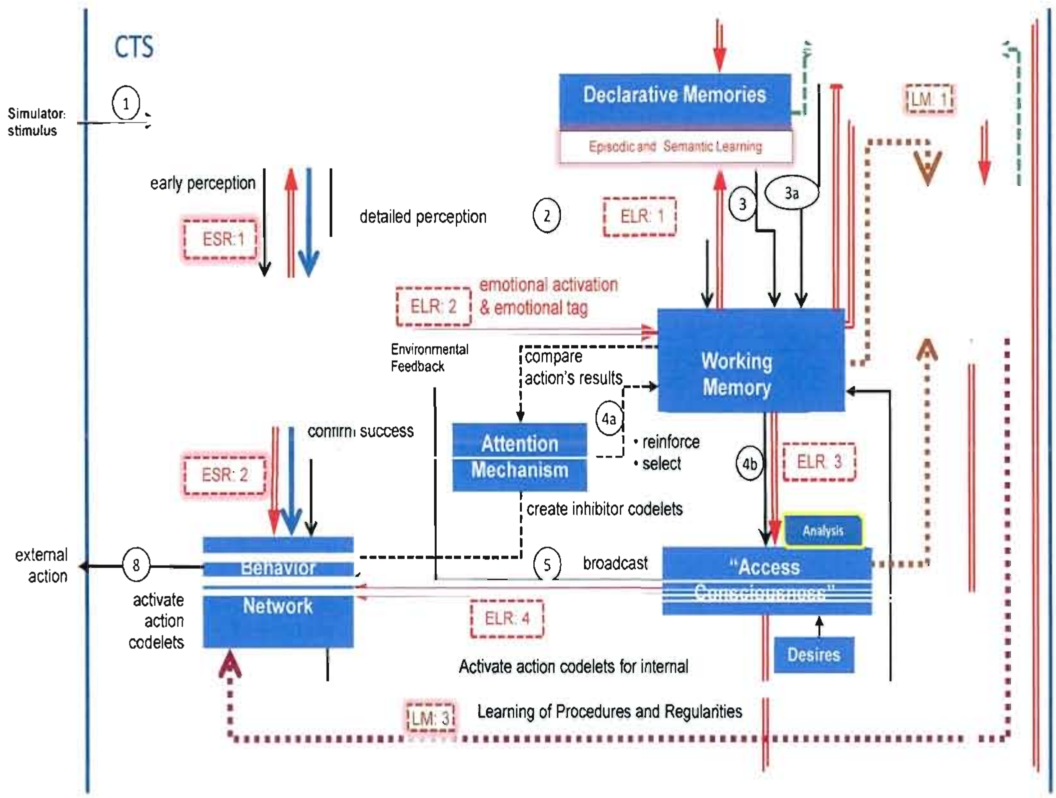

Figure 4.1 CELTS' Architecture with Emotion and Learning Mechanisms

If they see information coming in WM that confirms the Behaviour's expected result, they directly send reinforcement activation to the behaviour nodes that created them (that is, they do not do so through conscious broadcasting). This behaviour will thus see its base-level activation heightened, making it a more likely choice in a similar context. In the case of a failure to meet expected results, however, relevant resources need to be recruited, to allow them to analyze the cause of the failure, to correct the previous emotional interpretation of the situation, and to allow deliberation to take place concerning supplementary and/or alternative actions. The expectation codelets then work to have discrepancies brought to the attention of the whole system (in an eventual conscious broadcast of the noted discrepancy) by sending the information to the CELTS' WM. After sending the information to WM, CELTS continues through its cognitive cycles (see next section, step two to eight of the cognitive cycle) to allow for improved decisions.

The expectation codelets' second duty concerns our "pseudo-amygdala" (the Emotional Mechanism), in cases where it forced an automatic reaction through the short route (e.g., the imminent collision in the virtual world). Indeed, when low-level basic information coming from the perception codelets recognize aspects of the situation as highly dangerous, there is no time to think and, through the mechanism described above, the emotional codelets will force an action to fire in the Behaviour Network. This makes CELTS jump before thinking (James, 1884) (ESR's path, red-dotted rectangles and blue arrows which demonstrate primitive appraisal in Figure 4.1). That is, it makes CELTS act before it had time to become "conscious" of the situation and consciously plan a course of action. This corresponds to the first reaction taken by CELTS in our aforementioned example about imminent collisions in the virtual world.

However, the instantaneous, mindless reflex must be evaluated following the more thorough analysis of the situation that comes later, through the long route. CELTS can do this because both the short and long routes process the information in parallel. In fact, instinctive reactions execute faster. Eventually, however, a conscious broadcast of information (step 5 of CELTS' cognitive cycle), which gives CELTS a better idea of the situation, allows normal action selection to take place. When the action thereby proposed comes into WM (step 2 of the cognitive cycle), the expectation codelets compare it to the reflex action that has been prompted. If roughly in correspondence, they put into WM a confirmation to the effect that the initial reaction was right, which will serve, when broadcast, as a reinforcer to the emotional codelet(s) that were instrumental in setting off the reflex. In effect, this will make our pseudo-amygdala reinforce the relevant rules and nodes. However, when the initial reaction diverges from the behaviour proposed by the more detailed analysis, the pseudo-amygdala has to alter its first reaction. This corresponds to step two in our example about imminent collisions. From a neurological point of view, control over actions is the role of cortical areas. In CELTS, the expectation codelet that determined that the action taken by the short route was inappropriate subtracts some activation (this process is explained in the section 4.1) from the codelets in the Emotional Mechanism responsible for the direct implicit reaction. Activation will also be subtracted to the corresponding nodes in the BN that executed the action.

This way of implementing the control, as we will see below, seems in accordance with the fact that the amygdala never unlearns a "rule," especially for very dangerous stimuli, and always reacts to a given stimulus (Squire and Kandel, 2000, Rolls, 2000). This description highlights the fact that CELTS' Emotional Mechanism, which responds implicitly to events, reacts faster than the conscious process, but may react in ways that are different from what conscious planning would decide. Emotional codelets receive reinforcements from the environment (via expectation codelets) and can learn or, as we will explain in the next section, create new nodes for the actions they took. In the next section, we explain how the Emotional Mechanism influences CELTS cognitive cycle.

4.1.1 Impact of Emotions in CELTS' Cognitive Cycle

The emotional long route involves the consciousness mechanism. Emotions influence this mechanism at every step in the cognitive cycle. We briefly recall each step in the cycle and then, in italics, explain how the valence attributed to situations by CELTS' Emotional Mechanism influences it. For a visual representation of the described process, please refer to Figure 4.1.

Step 1: The first stage of the cognitive cycle is to perceive the environment; that is, to recognize and interpret the stimulus (see (Dubois et al., 2007) for more information).

All incoming information is evaluated by the Emotional Mechanism when low-level features recognized by the perceptual mechanism are relayed to the emotional codelets, which in turn feed activation to nodes in the Behaviour Network. Strong reactions from the "pseudo-amygdala" may cause an immediate reflex reaction in CELTS (Squire and Kandel, 2000, Purves et al., 2008).

Step 2: The percept enters Working Memory (WM): The percept is brought into WM as a network of information codelets that covers the many aspects of the situation (see (Dubois et al., 2007) for more information).

In this step, if the received information is considered important or dangerous by the Emotional Mechanism (EM), there will be a direct reaction from EM which primes an automatic behaviour from BN (Rolls, 2000, Squire and Kandel, 2000, Purves et al., 2008).

Step 3: Memories are probed and other unconscious resources contribute: All these resources react to the last few consciousness broadcasts (internal processing may take more than one single cognitive cycle).

What is brought back from episodic memory is evaluated by the emotional codelets (ELR Figure 4.1) and receives its emotional load anew.

Step 4: Coalitions assemble: In the reasoning phase, coalitions of information are formed or enriched. Attention codelets join specific coalitions and help them compete with other coalitions toward entering "consciousness".

Emotional codelets observe WM's content, trying to detect and instil energy to codelets that, they "believe," require it, and attach a corresponding emotional valence. As a result, emotions influence which information comes to consciousness, and modulate what will be explicitly memorized.

Step 5: The selected coalition is broadcast: The Attention mechanism spots the most energetic coalition in WM and submits it to the "access consciousness," which broadcasts it to the whole system. With this broadcast, any subsystem (appropriate module or team of codelets) that recognizes the information may react to it.

Steps 6 and 7: Here unconscious behavioural resources (action selection) are recruited. Among the modules that react to broadcasts is the Behaviour Network (BN). BN plans actions and, by an emergent selection process, decides upon the most appropriate act to adopt. The selected Behaviour then sends away the behaviour codelets linked to it.

In this step, the emotion codelets stimulate nodes in the BN, preparing it to react, priming certain behaviour streams, and thereby increasing the likeliness of their firing. This mostly mimics priming effects. The emotional valence (positive or negative) attached to the published coalition will influence how resources react. When the BN starts a deliberation for action, for instance to build a plan, the plan is emotionally evaluated as it is built, the emotional codelets playing a role in the selection of the steps in the plan. If the looping (through the cognitive cycle) concerns the evaluation of a hypothesis, the emotional codelets give it an emotional evaluation, perhaps from learned lessons from past experiences.

Step 8: Action execution: Motor codelets stimulate the appropriate muscles or internal processes.

Emotions influence the execution, for instance in the speed and the amplitude of the movements.

4.1.2 How CELTS' Emotional Mechanism Learn

After having proposed an Emotional Architecture for CELTS in the previous section, we explain here how emotional implicit and explicit learning are implemented in CELTS' architecture. In CELTS' cognitive cycles, stimuli from the virtual world simultaneously go to WM and EM. The latter detects events of emotional importance. Our implementation of implicit emotional learning is inspired by the views of Drew Westen (Westen, 1999) and those of Larry Squire and Eric Kandel (2000), while that of explicit emotional learning is inspired by Cannon's theory (Cannon, 1927).

Implicit emotional learning occurs when EM's nodes reaction intensity (EIS, Eq. 1) or the strength of its connections to nodes in WM or BN is modified. In the implicit emotional learning phase, the influence of emotional codelets (either those temporary resident in WM or those situated in EM and listening to the received information) through their base level activation indirectly affects the creation of coalitions and their selection (step 5) by the Attention Mechanism (steps 3 and 4 of cognitive cycle). Thus, the Emotional Learning Mechanism (ELM), in its implicit learning phase, learns (see below) which coalition in WM received emotional energy from EM. This occurs when emotional codelets resident in WM try to detect which coalition, according to the agent's goal, is emotionally more important than others and then by attaching themselves to those coalitions, which thereby instils a portion of its energy to it. This may increase the likeliness of those emotionally selected coalition to draw Attention (i.e., AM) upon itself in the upcoming cognitive cycles. Moreover, ELM learns (see below) that it must send energy to these emotional codelets in WM to prolong the coalition's lifetime in WM and to help them be selected by AM. This is due to the fact that codelets with no energy will exit WM. Thus, in this way, the emotional codelets detected as emotionally important by EM will remain active in WM to attach themselves to coalitions. This emotionally learned information will never be forgotten by the system (Westen, 1999, Squire and Kandel, 2000)

Explicit emotional learning occurs following the broadcasting of information (step 5 of cognitive cycle) in the system. In the explicit emotional learning phase, if for a given situation, the information coming to WM that was considered as very important by perceptual nodes (Step4 of cognitive cycle), EM detects no emotionally important information, it will create a new, empty node with a context which describes ongoing events. To fill out the action part of the new node, EM will wait for the consciously-mediated selection of a behaviour and the ensuing broadcasting of the event with external confirmation after the execution of the action by CELTS. If the selected action from BN received a strong (positive or negative) reinforcement from the environment, EM learns the broadcasted information instantaneously, that is, in less than a second (note that CELTS processes information through cognitive cycles, which happen five times per second (Franklin and Patterson, 2006)). At this point, EM has associated the context of the new node with the action selected and executed by CELTS. Information brought to consciousness right after the action took place becomes the result part of the created node.

Each new node in EM includes a context, an action, a result, a cause, a base-level activation and a reaction intensity. Learning in each node happens very fast (especially in the case of fears) by strengthening the node's activation according to a sigmoid function. To simulate EM's codelets behaviour, we input three parameters into a sigmoid function (Eq.1): (1) ω ,the codelet's base-level activation; (2) β , the learning rate; (3) λ ,controls the emotion activation, which means that if intensity goes beyond this threshold, the corresponding codelet in EM will release its output (positive or negative energy) into the system. The sigmoid function is used in order to map the three parameters unto a 0 to 1 range and allow each codelet to react, giving CELTS the ability to implicitly and explicitly act on the situation.

The emotional codelet's reaction intensity corresponding to the stimuli at the time t is calculated by:

$$EIS = \frac{1}{1+e^{(-EIS_{t-1}*\beta*\lambda*\omega)*\Delta t*C}} \qquad \text{(Eq. 1)}$$

- EIS_{t-1} is the value of intensity for emotion at the previous step
- λ threshold for emotional activation release
- ω base-level activation
- β a constant in [0,1] for learning purposes
- C the number of cognitive cycles
- Δt actual time minus the last time the program was executed

Implicit emotional learning in EM occurs through this update of the node's reaction intensity (*EIS*). Recall again that this fast emotional learning can bring a direct reaction (before information is broadcasted) as when fear or a very high emotional level makes an agent react instantaneously. This type of learning helps CELTS learn to react faster to the next similar or identical situation. However, if CELTS was disposed to react very strongly, but it turns out that the agent should not have reacted that strongly, it can modify its reaction intensity for the next occurrence, once again according to the sigmoid function. To do this, the Emotional Mechanism creates one emotional codelet (named a_i, as in the pseudo-amygdala) for each very important stimulus s_i calling for an emotional response, with a connection weight w_i between them. The output of each emotional codelet is primarily obtained by the following equation:

$$a_{iec} = s_i * w_i * EIS \qquad \text{(Eq. 2)}$$

Usually, CELTS recognizes a situation instantaneously and will react in an appropriate time frame. However, sometimes, CELTS may need more time to deal with the situation. Maybe it has no behaviour ready to offer a reaction; maybe it entered a deliberation to establish a probable cause, or to decide what to do. But as the number of cognitive cycles (C) increases without resolution, the emotional salience of the stimulus increases (as when we get more nervous waiting for a solution with each passing moment). Emotional codelets thus increase their output until they receive a signal from expectation codelets telling them whether they reacted appropriately, or until they set-off a reflex action. However, an emotional codelet may connect or react to some different perceptual nodes each sending its activation (a_{ipc}) to the emotional codelet. We may then calculate the emotional codelet's energy as the sum of all perceptual inputs to it according to Eq.3. An emotional codelet's energy is thus:

$$E_A = \sum a_{ipc} * C \qquad \text{(Eq. 3)}$$

If, however, EM learned some particular events as being of highest emotional importance, it will cause a direct (and intense) reaction for the next similar event. It may turn out, however, that following the execution of the action, CELTS determines, through its cognitive cycles, that such events are not emotionally important (or not that important). This occurs for instance when CELTS observes a collision-risk situation brought about by the astronaut in the virtual-world and reacts directly and too intensively. After some time, it understands that the reaction was wrong or too strong. If that situation repeats many times, then the emotional salience of that situation for reaction will be diminished. In this case, EM might re-adjust w_i to diminish the importance of the stimulus toward a response. If it happens many times, EM will end up classifying the stimulus as neutral information, giving it a neutral valence. The opposite situation may happen when information enters WM and is considered normal (neutral) by EM, but it turns out that after a conscious broadcasting followed by an action, CELTS receives strong reinforcement feedback (positive or negative). At this point, the system again may readjust w_i for the corresponding nodes. Learning in this second sense (w_i adjustment) can happen by calculating the difference between the reinforcer (R) and the activation (a_i) of the emotional codelet:

$$\Delta w_j = \beta * Si * [R - \sum a_i] \qquad \text{(Eq. 4)}$$

The R represents the astronaut's good or bad manipulation of Canadarm2 or the correct or false answers to the questions given by CELTS. The β parameter is used as a standard learning rate parameter, settable between 0 (no learning) and 1. However, the emotion present in CELTS will decay by losing a fixed portion of energy if the actual emotion receives little attention in the following cognitive cycles. This "peripheral-central" model of emotional learning implemented in CELTS is what all other models failed to propose.

4.1.3 How CELTS' Emotional Mechanism helps other types of Learning

CELTS has both implicit and explicit learning. CELTS' learning mechanisms are implemented in a distributed and modular manner with emotions influencing all of them. They are Emotional learning, learning of regularities (Faghihi et al., 2007), Procedural learning (Faghihi et al., 2007), Episodic learning and Causal learning. The implicit learning is unconscious and independent of the Attentional Mechanism (AM). It occurs in the the Emotional Mechanism (EM), the Working Memory (WM) and the Behaviour Network (BN), whereas explicit learning occurs in different learning modules after information is broadcasted by the access consciousness (step 5 of cognitive cycle). In this part of our document, we briefly detail how emotions influence implicit and explicit learning in CELTS. More precisely, we focus on the influence of emotions in the learning of regularities and in procedural learning. This will be discussed in the context of Episodic and Casual learning in the following chapters.

4.1.4 Implicit influence of emotions in the learning of regularities in WM and BN

When the emotional valence attributed to an encountered situation is weak[15], its influence in the learning of regularities will be implicit. It will not be sufficient to trigger codelet firing in the BN or to take WM coalitions to consciousness.

When virtual world information is sent to CELTS, it eventually reaches WM (step 2 of cognitive cycle). Both implicit and explicit learning processes start at this point in parallel. Implicit learning of regularities in WM essentially comes from the reinforcement of the links between codelets based on the time they spend together in a coalition. Following Baars (Baars, 1997), this occurs when associations between codelets and their base level activation indirectly affect the creation of coalitions and may, in the following cognitive cycles, cause the Attention Mechanism (AM) to select them (steps 3, 4 and 5 of cognitive cycle) (e.g., the retrieval and selection of the information). EM, among others, influences WM's content by detecting and instilling a portion of energy (positive or negative, which is described as E_{Ai} in Equation 5) to a particular coalition. This may increase the likeliness that the emotionally selected coalitions draw Attention (i.e., AM) upon themselves in subsequent cognitive cycles. The emotional influence in WM's content is simulated with Equation 5. The weights of the links between codelets in a coalition are adjusted in accordance with the learning parameters and the energy received from EM. It must be noted that Equation 5 is used to simulate the influence of EM in CELTS' WM content (see

[15] Thresholds are approximately < 0.5 for positive cases and >-0.5 for negative cases.

(Faghihi et al., 2007) for more information) whereas Equation 1 in the previous subsection is used to simulate EM's behaviour nodes situated in EM.

More precisely, CELTS' implicit learning of regularities in WM establishes which codelets already have connections with others, which are selected by the Emotional Mechanism (EM) and which have received supplementary energies. It then creates new links or reinforces the existing ones between the codelets within a coalition in WM. This can increase the likelihood that certain coalitions are chosen by AM in future cognitive cycles.

$$Strength = \frac{1}{1+e^{(-sx*EAi+d).t.C}} \qquad \text{(Eq. 5)}$$

Where:

-*x*: association strength between two codelets
-*s*: rate of increase of base-level activation (for the links between codelets)
-*d*: threshold value for conversion into a coalition
-*C*: the number of cognitive cycles since the creation of the link.
-*t*: mean time for two codelets passed together in WM.

CELTS' implicit procedural learning takes place in the BN — for both links between nodes and the base-level energy of each node (Faghihi et al., 2007). When energy passes through the link between two behaviour components in the BN, it will strengthen. Transferring more energy between the links in the BN also increases the accumulation of the node's base-level energies, which alter the nodes' reaction intensities in subsequent cognitive cycles. The re-execution of the behaviour items having had received emotional energy increases the strength of their links and speeds up their execution time in the future. Thus, this type of learning accelerates planning and behaviour sequence execution (Faghihi et al., 2007). CELTS' implicit procedural learning detects behaviour codelets that were selected by the Emotional Mechanism (EM) and have received supplementary energy in the BN Figure 4.1, red plain arrows). It must be noted that in our model, emotion does not suddenly appear and disappear. The energy from EM is instilled in a constant manner for the subsequent cognitive cycles if the same stimulus comes to the WM. Depending on the received information and emotional primary evolution of the situation (such as collision=high-threat or, collision-risk=medium-threat, camera-adjustment=low threat), EM produces a valence reaction.

The instilling of Emotional energies also remains constant during the learning phase. Thus, depending on the received energies from the emotional mechanism, CELTS can learn faster or may learn normally (Faghihi et al., 2007).These emotional interventions, which allow concepts to be selected faster by the Attention Mechanism for broadcasting by the Access consciousness (Step5 of cognitive cycle), also allow the various aforementioned CELTS' Learning mechanisms to learn at a faster pace.

4.1.5 Explicit influence of emotions in the learning of regularities in WM and BN

The explicit influence of emotions in the learning of regularities in WM and BN is related to the energy that is instilled from EM to the nodes. This energy alters their base-level energies and is enough to directly fire them in the BN or bring coalitions from the WM to consciousness.

Explicit learning in WM occurs when AM makes a collection of codelets into a coalition that is broadcasted. This occurs in various forms and locations in CELTS, for instance in the learning of regularities, Episodic learning and Causal learning (see the following chapters). The explicit learning of regularities implemented in CELTS rests on a bottom-up theory for data categorisation inspired by Hebbian learning and Jackson's Pandemonium theory (Jackson, 1987). If the reappearance of a coalition occurs frequently in WM, the coalition is likely to be relevant for CELTS (this, we refer to as a "regularity phenomenon", see (Faghihi et al., 2007). Thus, it is likely that these coalitions eventually reach a permanent coalition status to represent this regularity (for example, Canadarm2 rotation that indicates repetitive reversals of motion show a user's difficulty with a manoeuvre). The influence of emotional learning in this stage lies in its direct intervention in WM. In effect, it directly instils positive or negative valences to specific coalitions thus causing AM to immediately select them and consciousness to subsequently broadcast them.

EM also influences BN by its direct intervention. In some dangerous cases, as aforementioned, EM intervenes directly by instantiating corresponding behaviours to solve a problem.

4.2 EVALUATION AND RESULTS

We compare the performance of CTS' original architecture with that of its new version, CELTS equipped with EM. How EM's explicit and implicit reactions alter BN energy levels will be detailed in the next chapter.

Equipped with the Emotional Learning mechanism, CELTS is capable of better decision making and more accurate interventions than CTS. To validate CELTS' EM capacity when faced with dangerous situations, we integrated it into *CanadarmTutor* (Nkambou et al., 2006), our simulator designed to train astronauts to manipulate Canadaram2. CELTS' interpretation of a given situation is in part dependent on *CanadarmTutor*'s interpretation of the users' actions in the virtual world.

CELTS' performance was tested in various situations such as collision risk, collision, good and bad manipulations of Canadarm2. We ran CELTS executions randomly and noted reaction times and the decisions made. We predicted that CELTS should be more adaptive than CTS in any given situation.

It should be noted that at this stage, we only discuss very dangerous and dangerous situations in which EM must intervene explicitly in WM and BN. Furthermore, we wish to examine the adaptiveness of CELTS' EM when faced with very dangerous situations. For other types of emotional interventions, such as while CELTS interacts with users to help them learn to manipulate Canadarm2 in the virtual world, and also for how emotions can bring CELTS to a self-satisfaction state, readers are referred to the next chapter.

Situation one: Collision risk

To addressee this situation we executed CELTS with and without EM. Suppose that a user is asked to move Canadarm2 from configuration A to configuration B on ISS. CELTS must recognize which movements will not cause collisions. CELTS then gives the user feedback in the form of questions or hints.

Execution without EM:

In this situation, suppose that the user has brought Canadarm2 too close to ISS. The simulator immediately informs CELTS (Figure 4.3) that there is an imminent risk of collision. The information is then selected by CELTS' attention mechanism and broadcast to the system. After deliberation from CELTS' BN, an act will be chosen and shown to the user (Figure 4.2). To react to this situation, CELTS uses the long route. No significant changes are made to the energy in the BN (see next chapter for more details).

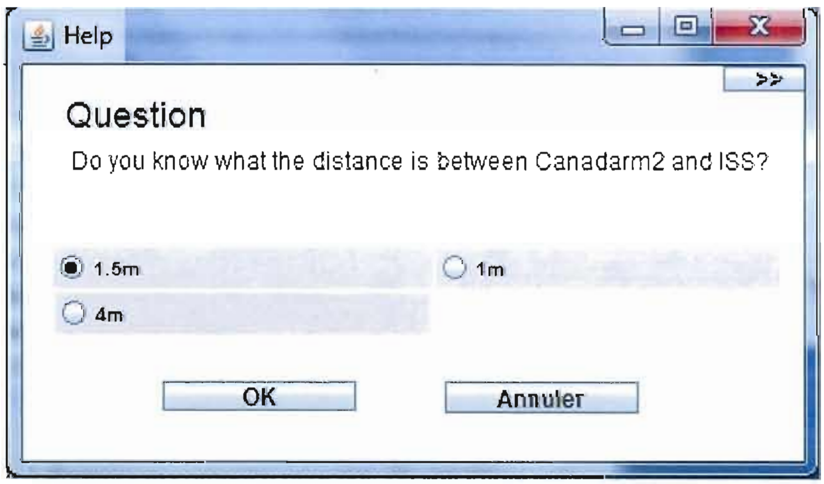

Figure 4.2 Message whitout Emtoinal intervention

Execution with EM:

Part one (situation 1.1): in this situation, suppose that the user has brought Canadarm2 too close to ISS. The simulator immediately informs CELTS (Figure 4.3) that there is a risk of an imminent collision, and that these collision risks are coded as very dangerous. As a result, EM's codelets react to the situation by instilling enough negative energy (equal to -0.9, a very negative valence) to the corresponding behaviour in the BN to make it fire. The BN reacts to the situation by prompting the message to the user: "Stop moving the arm. This is a very dangerous situation. Answer the following questions before moving on." (Figure 4.4). Because this situation is attributed a high emotional valence (high-threat situation), CELTS' short-route is activated.

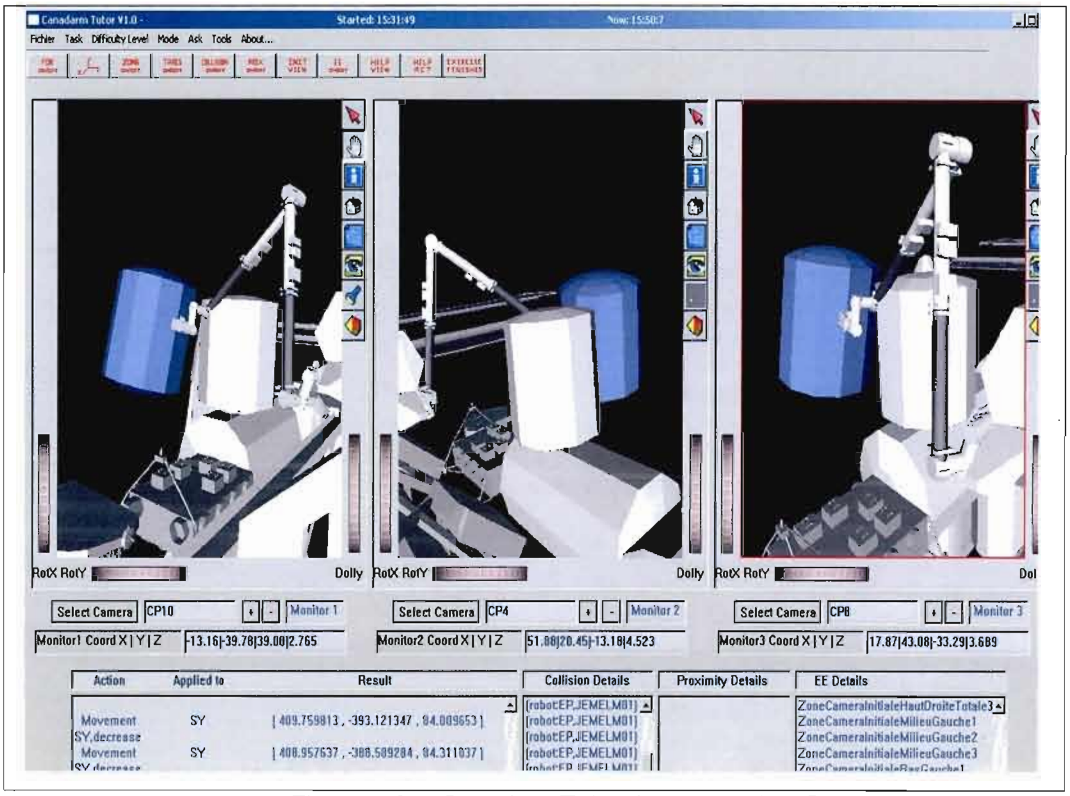

Figure 4.3 CanadarmTutor demonstrating Collision

In parallel, CELTS' long-route also activates. As a result of the high emotional valence, the collision risk information received from the virtual world is more attentively examined. CELTS then asks the user the following question: "Do you know what the distance is between Canadarm2 and ISS?" (Figure 4.2). If the user answers correctly, the emotional codelets' intensity decreases. The second question is "If you get closer to ISS, what will happen?" Again, if the user selects the correct answer, the emotional codelets' intensity converges to a positive value. This means that the user is an expert. Accordingly, the intensity of the emotional codelets that reacted to the collision risk must very rapidly, as demonstrated in Figure 4.5, reach a positive value. It must be noted that the cognitive cycles in Figure 4.5 represent the cognitive cycles in which the user responded to CELTS' prompts only. In Figure 4.5, the x and y axes indicate the cognitive cycles and the emotional codelets' intensity respectively. Remember that Emotional valences are between -1 and +1.

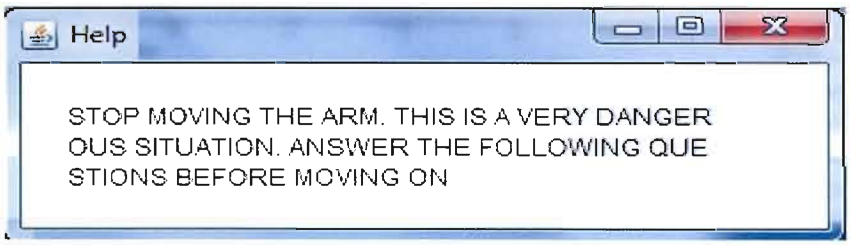

Figure 4.4 Short route reaction to the user1

On the contrary, if the user fails to answer, CELTS considers the user to be a beginner. The intensity of the emotional codelet that reacted to this event reaches -1, the highest negative value possible. At this stage, the user will be prompted not to perform any further movement and review the lesson. The emotional intensity will remain at -1 if the user does not stop manipulating the Canadarm2. If the user stops manipulating Canadarm2, the negative emotional intensity will reach zero after a number of additional cognitive cycles.

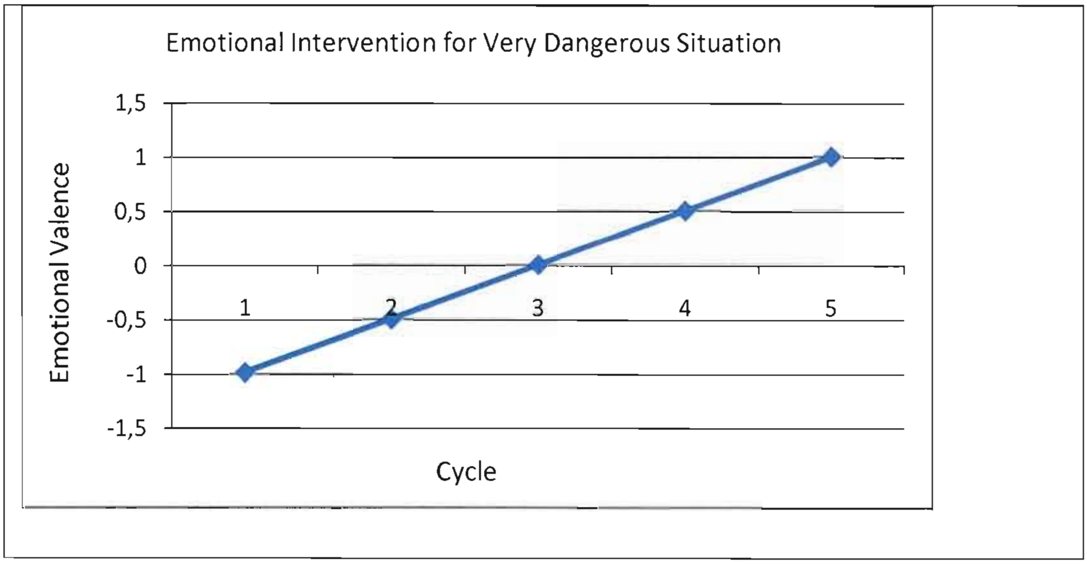

Figure 4.5 Emotional Intervention for very dangerous situation1

Part two (situation 1.2): in this situation, suppose that the user is manipulating Canadarm2 well. The emotional valence attributed to this user's Canadarm2 manipulation will be zero (Figure 4.6, cycle zero). EM's states vary depending on the user's performance in the virtual world. It also depends on the user's correct/false answers to the CELTS' questions asked while manipulating Canadarm2. It must be noted that at this stage, the short route is not engaged for reaction yet, because the user has not yet faced any dangerous situation in the virtual world. Thus, at this stage, the long route is responsible for all decisions made by CELTS. At some point, suppose the user does bring Canadarm2 too close to ISS, thus now facing the risk of collision. This risk of collision information will be transmitted to WM. EM's codelets will become more active. Importantly, their base-level activation may increase or decrease depending on the user's answers to CELTS questions regarding the cause of the mistake. The greater the number of wrong answers, the further EM's codelets activate and the more negative the valences assigned to WM's content will be. After a certain number of wrong answers, the short route activates. As in situation 1.1, EM's codelets directly instantiate corresponding nodes in the BN to prevent any collision in the virtual world. As indicated in Figure 4.6, the short route activation and the EM codelets' reaction to this situation occur in about four cognitive cycles. The

EM codelets' direct influence in WM and BM starts when their base-level energy reaches > -0.5 (Figure 4.6). Once the, emotional codelets react to the situation, the long route more attentively interprets the situation and proposes further solutions. For the rest of the situation, CELTS will behave as explained in situation 1.1

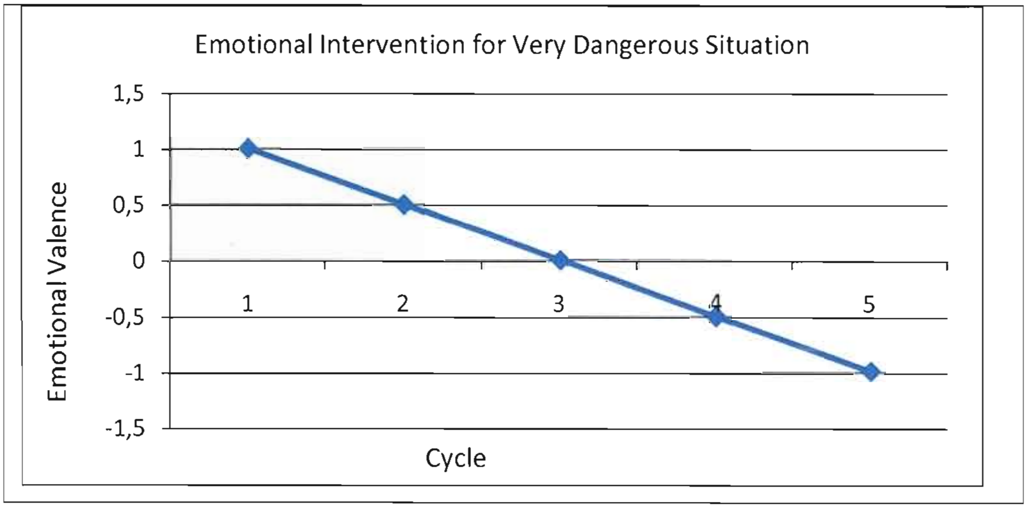

Figure 4.6 Emotional Intervention for very dangerous situation2

Situation two: camera adjustment

Another important task to be considered by users while manipulating Canadarm2, is choosing the best three cameras (from a set of about twelve cameras on ISS) for viewing the environment (since no camera offers a global view of the environment). Of course, forgetting camera adjustment is not as dangerous as collision risk. However, forgetting camera adjustment may lead users to manipulate Canadarm2 very close to ISS which in turn increases the risk of a collision with ISS.

Execution with EM: In this situation, let the initial emotional valence in this situation be zero (Figure 4.9). After a while, WM receives information indicating that the user has forgotten to adjust the cameras. Given that the information does not suggest a very dangerous situation but it is nonetheless important (see Figure 4.9), EM attributes a -0.5 emotional valence to it. In effect, it is important enough for CELTS' AM to select it and bring it to consciousness (long route). After deliberation, a hint reminds the user to perform Camera adjustment (Figure 4.7).

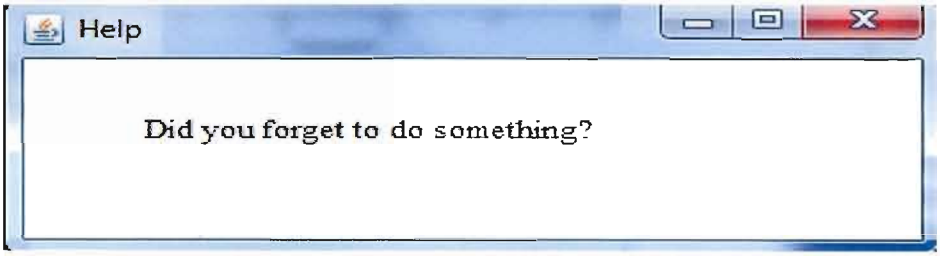

Figure 4.7 Forget to do something

At this stage, EM's codelets react indirectly to the situation. EM's codelets reaction depends of the outcome of the user-CELTS interaction. If CELTS' questions are correctly answered, (Figure 4.8), the intensity of EM's codelets for direct reaction will decrease. However, if the user does not answer CELTS' questions correctly, the codelets' intensity increases (see Figure 4.9). This negative valence increase will occur during every user-CELTS interaction or during any bad Canadarm2 manipulation. When the user finally understands the problem and adjusts the cameras, the EM's codelets negative energies will decrease.

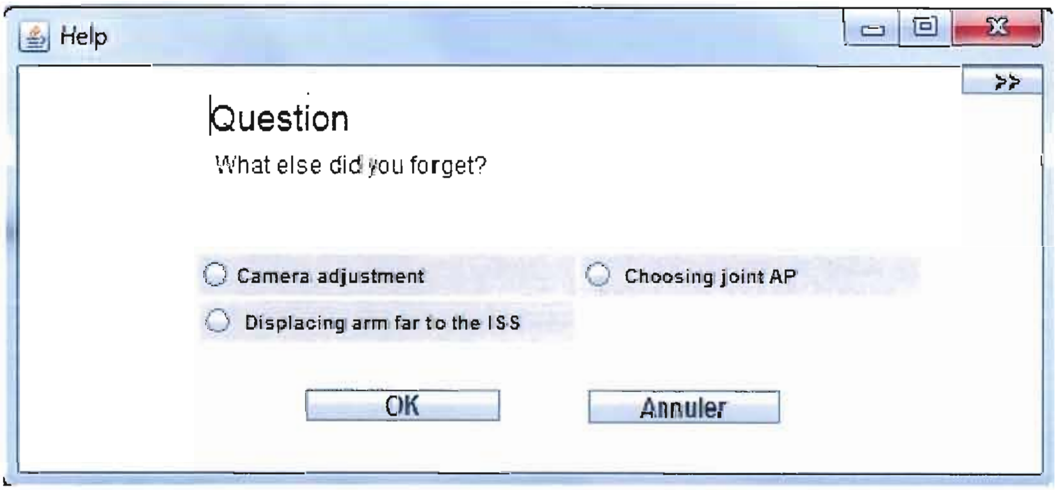

Figure 4.8 CELTS question to the user

If the user does not stop moving Canadarm2, EM's short route is activated, thus reacting directly to the situation, as explained in situation one. CELTS will react to the collision risks in the same manner as detailed in situation1.1.

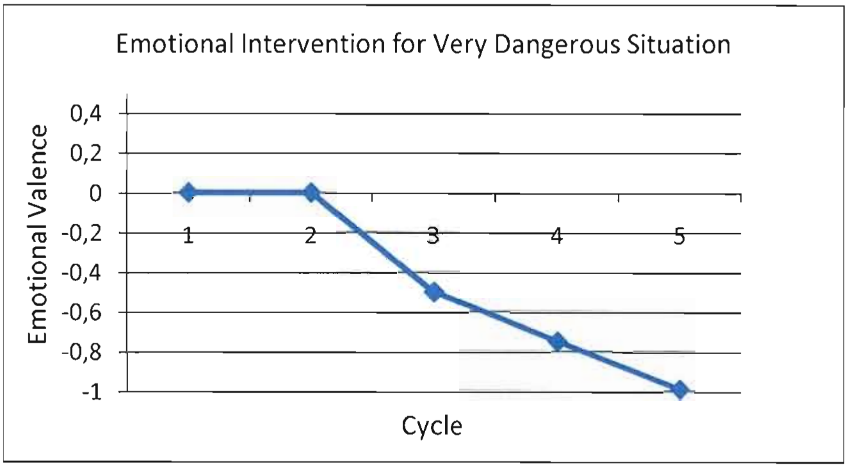

Figure 4.9 Emotional Intervention for very dangerous situation3

Execution without EM: In this situation, CELTS performs through its long route and interacts with users using Figure 4.7 and Figure 4.8 There will be no short route engagement even if the situation worsens.

Lastly, we will compare the reaction time of CELTS' BN and EM' codelets when faced with dangerous situations (Figure 4.10).

Figure 4.10 presents both the BN and EM reaction time when CELTS faces a collision risk. The first graph represents EM's reaction time when the short route is activated. In this case, the reaction time varies between zero and 17 millisecond. The second graph represents BN's mean reaction time when the long route is activated. In this case, the reaction time varies between 200 and 1400 millisecond. These experiments demonstrate that EM decreases CELTS' reaction time in dangerous situations.

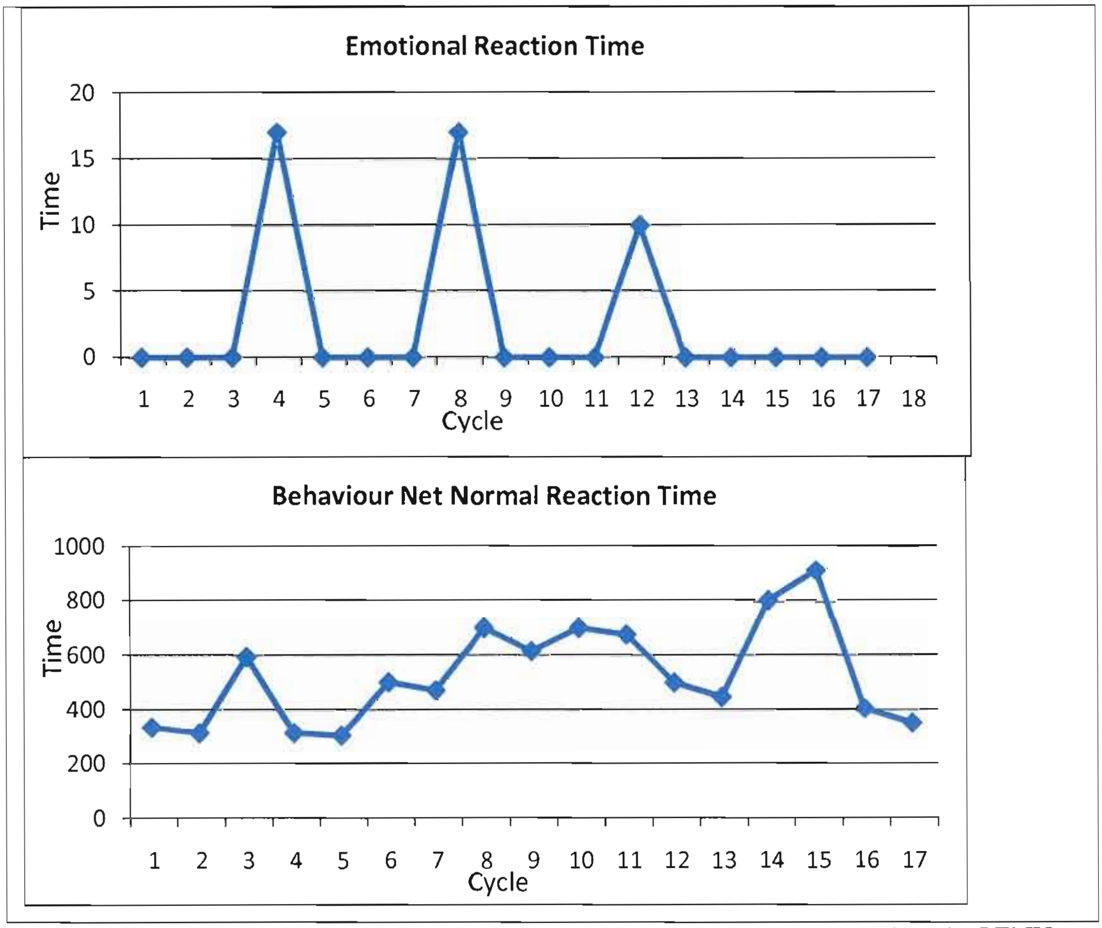

Figure 4.10 Comparison between normal and emotional-intervention reactions in CELTS.

4.3 CONCLUSION

In this chapter, we described how to implement a fundamental Emotional Mechanism (EM) in CELTS. We also detailed how EM interacts with CELTS' various components. The interactions occur, during consciousness broadcasting, and more specifically during the learning phase and during CELTS' reactions to outside stimuli. CELTS' emotional reactions occur both implicitly and explicitly. The resulting architecture is more neurologically plausible, for it integrates a recent view of the amygdala's double role in emotion. That is, this architecture is able to make CELTS learn and then react swiftly in emotionally-ladened situations as well as supply an emotional assessment to all sorts of stimuli in working memory, an assessment which may used for learning aims. This allows faster learning of emotionally assessed information that enters working memory and is later broadcasted through CELTS' cognitive cycles. As our experiments illustrate, CELTS, because of its emotional learning mechanism, may, when need be, react more swiftly than its previous versions (i.e., reacting sooner in the cognitive cycle). It is worth noting that through these experiments, CELTS' EM demonstrated the capability to easily adjust its emotional valences from negative to positive and vice versa, in any situation.

In the next chapter, we explain the implementation of episodic learning in CELTS and how it is influenced by emotions.

CHAPTER V

IMPLEMENTATION OF EPISODIC MEMORY AND EPISODIC LEARNING IN CELTS

In this chapter, we propose the implementation of an Episodic memory and an Episodic Learning Mechanism in CELTS, based on the current neuroscientific multiple-trace theory (Purves et al., 2008) detailed in chapter II. In our model, emotions play a role in the encoding and remembering of events. Emotions improve all types of learning as well as the agent's behaviour.

First, we briefly review CELTS' Episodic Learning Mechanism (EPL)[16]. EPL consists of (1) the pseudo-hippocampus, which encodes any given information coupled with its assigned emotional valence, and the agent's actions. EPL also has a process called (2) "*memory consolidation*" (Alvarez and Squire, 1994, Paré, 2003). This process intervenes in the memorization and the retrieval phases of events in CELTS' memory architecture. The memorization phase of CELTS' architecture includes emotional valences (Ortony et al., 1988) ascribed to ongoing events by CELTS' Emotional Mechanism (Faghihi et al., 2008a).

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[16] By episodic learning, we mean that CELTS is able to remember past episodes, which allows the agent to induce a potentially better adapted behaviour. By behaviour, we not only want to talk about visible stages but also mental events probably leading to the execution of a suitable action. If the action appears indeed (not) suitable, the agents associates a negative/positive valence to the episode which will improve, if similar one is presented, the speed and the relevance of the information to be chosen and executed by the system.

The memory consolidation phase consists of a process that constantly extracts temporal regularities from all past episodes to form an episodic memory. This process is very important because, as a cognitive agent, CELTS receives a huge amount of data, which is temporally related to its environment but that may or may not be relevant in the future. Moreover, much communication takes place between the different parts of the system. This again produces a large amount of internal data during each cognitive cycle. In order to be used in decision-making, all of this data must be consolidated into a smaller form. We found that CELTS requires the consolidation of huge amounts of sequential data, as is the case for mining frequent patterns in data mining. This suggests the use of sequential pattern mining (Agrawal and Srikant, 1995) as the basis for implementing the consolidation process. Sequential pattern mining is an efficient knowledge discovery technique that is widely used in computer science to find frequent temporal patterns among sequences of symbols when dealing with a huge amount of data, a common situation for CELTS. This, we believe, provides a functionally plausible memory consolidation model. The sequential patterns are useful in the retrieval (remembering) phase, to adapt CELTS' behaviour to past experiences. In the retrieval phase, a cue is introduced to all sequential patterns previously created by the system, making them active, each according to its similarity to the cue. The information sequence activated in parallel then reinforces the cue's content.

In the next sections, we first briefly review the existing literature on episodic learning in cognitive agents. We then provide a thorough explanation of CELTS' Episodic memory and the implementation of the three phases of the Episodic Learning Mechanism in CELTS' architecture.

5.1 COGNITIVE AGENTS WITH EPISODIC MEMORY

In this section, we first briefly review of the existing literature on episodic learning in cognitive agents. We then focus on the work of McClelland, McNaughton and O'Reilly (McClelland et al., 1995) to show how the hippocampus and the cortex play an important role in episodic learning and memory. As we'll see, the role of these two structures may be viewed as functionally equivalent to the recording and consolidation processes in our architecture.

Many researchers have attempted to incorporate episodic memory and learning mechanisms in cognitive agents and cognitive architectures (Najjar et al., 2005, D'Mello et al., 2006, Sun, 2003). Yet, they have either not included a role for emotions in the episodic learning and retrieval processes as of now (as is the case with CLARION and ACT-R) or no concrete implementations have been realized in the models proposed (the well-known ACT-R model for instance, has no explicit episodic memory). Instead, events are encoded as chunks in declarative memory, just like declarative information. During recall, beside the activation provided by the context, a base level activation function is used for each chunk to compute the probability of an information being retrieved and the speed of its retrieval. Basically, the activation is calculated based on the time elapsed since the last occurrence of the chunk in Working Memory (WM) and the number of times that the chunk was recalled. Because chunk activation decreases rapidly over time, after a short while, the frequency of chunk use becomes the most decisive feature for determining recall. Thus, ACT-R cannot recall information in a temporal context, and this induces abnormal behaviour (Najjar et al., 2005). In addition, since ACT-R has no emotions, these cannot be taken into account during episodic memorization and retrieval.

LIDA, as explained in chapter III, has an Episodic learning mechanism, which is influenced by its Emotional Mechanism. However, authors have not detailed what interactions between Episodic and Emotional Mechanisms occur in the implementation phase and there have been no concrete experimentations to demonstrate the strengths and weaknesses of the model in this respect (D'Mello et al., 2006).

The remainder of this section will address McClelland et al.'s (1995) connectionist model of episodic and declarative memory systems (we shall only be concerned with episodic memory).

Since CELTS is not implemented in neural networks but in a classical symbolic system, we finally assess what kind of processing is achieved by these neurological structures (as understood through the connectionist model) in order to see if that kind of processing can be implemented in CELTS. Because our episodic memory mechanism must be included in a fully functional agent, the advantage of this resulting architecture over McClelland et al.'s is that the complete process is modeled, including episodic memory recall. Moreover, our episodic memory includes the well-known influence of emotions, something that is absent in McClelland et al's.

McClelland et al. (1995) devised their neural network model of the interaction between the hippocampus and the neocortex to explore the standard consolidation model of episodic memory, and the peculiar pattern of memory loss that results from removal of the hippocampus. In order to understand the model, it must be noted first that, although it is located under the cortex, the hippocampus functionally is where cortical sensory processing ends up. Information from the senses enters dedicated modal areas (e.g. the occipital cortex), then goes to the association areas of the temporal and parietal lobes, and then finally go to the hippocampus (among other structures). Thus, information entering the hippocampus is fully processed by the cortex. McClelland and his colleagues hypothesize that the cortex is organized as a multilayer perceptron, a type of network that has been shown to categorize information in hierarchical prototype structures (Rogers and McClelland, 2006) when the information is represented by distributed and superposed representations (Rumelhart et al., 1986, Hinton et al., 1986) and when the network is trained by a gradient descent procedure (such as the backpropagation algorithm). If they are right, this means that information leaving the cortex to enter the hippocampus is fully categorized. However, multilayer perceptrons trained by gradient descent exhibit what has been called catastrophic interference (McCloskey and Cohen, 1989): new information can only be included in the hierarchical category structure developed as a result of initial learning if all (or a representative sample) of the *initial* training set is presented along with the new information. If it is not, that is, if the new information is presented alone, the category structure learned by the network is completely obliterated in favour of the category structure extracted from the new information. To prevent this, McClelland et al. (1995) give their cortical module a very low learning rate. Information processed by the cortex barely leaves a trace. This explains why, as H.M.'s case showed (Milner et al., 1998, Milner, 1966), the cortex cannot form declarative memories on its own and needs a complementary structure such as the hippocampus to do so.

The low learning rate of cortex leaves the initial storage of information to the hippocampus. This structure, they propose, implements a pattern associator and an autoassociator and learns following hebbian principles. However, as is well known, hebbian learning works best when information is borne by orthogonal representations. There is physiological evidence that the hippocampus's dendate gyrus is built to orthogonalize information through sparcification and competitive learning (Rolls et al., 1997) (O'Reilly et al., 2000). Accordingly, their model hippocampus contains a submodule that sparcifies and separates representations through competitive learning. Once it has been thus orthogonalized, information from various sensory regions of the cortex can be associated instantly (one shot learning) by Hebbian learning with a high learning rate. Patterns of categorized but reduced information from the various senses are thus associated (storage) and can be reactivated by having a sufficient portion of the original pattern reactivated (part of the recall process). The physiology and architectonic structure of the hippocampus suggests that CA3 (Cornu ammoni 3, a specific part of the hippocampus) may be implicated in these processes. Once a pattern has been reactivated, McClelland et al. posit that it can be reconstituted into a distributed pattern by a process similar, but inverse, to the one that orthogonalized it initially (CA1 and the enthorinal would be implicated here), after which it can reactivate the association areas of cortex all the way, occasionally, to its modal areas.

Reactivation of the cortex by de-orthogonalized signals coming from the hippocampus serves two functions. First, and what concerns us here, it serves as a memory of the event that was originally stored in the hippocampus. Such, according to McClelland et al.'s model, is the neurological basis of episodic memory. Second, it serves in the slow process of consolidation by helping mould the cortex' slow learning synaptic connections through a process they call interleaved learning. Much of McClelland et al.'s is dedicated to explaining how this process works, how it builds hierarchical categorical structures and how it solves the problem of catastrophic interference. We shall not describe this part of their model since our objective has been reached: we have described a neurocomputational model of episodic memory. However, it should be noted before we turn to our next task that the gradual building of the hierarchical categorical structure means that, over time, similar patterns coming from the senses will be categorized differently, that is, in a richer manner, category wise, and that it is this more richly categorized information that will be stored in the hippocampus henceforth. Our task now is to assess what kind of information is thus processed by the described-above structures in order to implement similar processing in CELTS. We first saw that information is recorded in some brute form (in the hippocampus) and that consolidation in long-term memory involves extracting relevant information from this brute recording.

5.2 EPISODIC MEMORY AND LEARNING IN CELTS

Episodic Learning (EPL) in CELTS starts when the information codelets that have entered in WM are chosen by the Attention mechanism and broadcasted by the consciousness mechanism. CELTS' *pseudo-hippocampus* (PH) learns all broadcasted information during each cognitive cycle. This corresponds to the brute recoding phase of McClelland model (McClelland et al., 1995). This learning happens through the creation of new sequences of events. Each sequence may contain one or more nodes that have links to other nodes situated in the sequence. Learning occurs through the strengthening/weakening the energy of the nodes and of the links between them. If the PH does not have a response set for the information broadcasted by the consciousness mechanism, it creates a new sequence with a unique ID and then creates an empty node with a context corresponding to the ongoing situation (current event). As it observes all information broadcasted by the consciousness mechanism, PH gives a unique ID to each coalition broadcast in the system and saves these IDs instantaneously. To fill out each node, PH waits for the consciously-selected behaviour and the ensuing broadcasting of the confirmation by the user of the correctness of the chosen behaviour. At this point, each node in the sequence is assigned the time of the broadcasted coalition, its total emotional valence, and a key-information-codelet (trigger-codelet) associated to the broadcast coalition that fires the stream of behaviours (if the trigger codelet has exceeded its threshold value). The PH then associates the context of the new node with the ID of the broadcasted coalition consciously-selected by the Attention Mechanism and executed by CELTS' Behaviour Network (BN). The sum of the emotional valences of the nodes belonging to the broadcast coalition is also saved. At this point the information is ready to be integrated into the different memories of the system. The sequence(s) related to this episode are saved in a database which is considered as CELTS' Episodic memory. This distributed information, as well as the distributed information learned by EPL (i.e. learning of regularities (Faghihi et al., 2007), by procedural learning (Faghihi et al., 2007) and by emotional learning (Faghihi et al., 2008b) during arm manipulation is then integrated in the same database separately. With this method, CELTS can relate an episode to its corresponding procedures in the BN.

We now describe how episodic learning takes place through CELTS' cognitive cycle.

5.2.1 Impact of Emotions and Episodic Learning in CELTS' Cognitive Cycle

As explained in section IV, two routes are possible in CELTS' cognitive cycle - a short route (the blue arrows) and a long route (black arrows). In both cases, the cycle begins with the perceptual mechanism. Hereafter, we briefly summarize each step in the cycle and in *italics*, describe the influence of the CELTS' *pseudo-amygdala* or EM and/or that of *pseudo-hippocampus* (PH). For a visual representation of the described process, please refer to Figure 4.1.

Step 1: The first stage of the cognitive cycle is to perceive the environment; that is, to recognize and interpret the stimulus (see (Dubois et al., 2007) for more information).

EM: All incoming information is evaluated by the Emotional Mechanism when low-level features recognized by the perceptual mechanism are relayed to the emotional *codelets, which in turn feed activation to emotional nodes in the Behaviour Network (BN). Strong reactions from the "pseudo-amygdala" may cause an immediate reflex reaction in CELTS.*

Step 2: The percept enters Working Memory (WM): The percept is brought into WM as a network of information codelets that covers the many aspects of the situation (see (Dubois et al., 2007) for more information).

EM: in this step, if the received information is considered important or dangerous by EM, there will be a direct reaction from EM which primes an automatic behaviour from BN.

PH: PH also inspects the information received by CELTS' WM. It then fetches relevant information in both WM and LTM and sends it back to WM once enriched. Relevant traces from the different memories are thus automatically retrieved. These will be sequences of events in the form of a list relevant to the new information. The sequences of events include the current event and the residual information from previous cognitive cycles in WM. These retrieved traces are made of codelets links to other codelets. Each time new information codelets enter WM, the memory traces are updated depending on the new links created between these traces and the new information codelets. This first involvement of the PH implements the context-giving role of episodic memory.

Step 3: Memories are probed and other unconscious resources contribute: All these resources react to the last few consciousness broadcasts (internal processing may take more than one single cognitive cycle).

EM: What is brought back from episodic memory is evaluated by the emotional codelets (as part of emotional intervention ELR: 2 in Figure 4.1) and receives its emotional load anew.

Step 4: Coalitions assemble: In the reasoning phase, coalitions of information are formed or enriched. Attention codelets join specific coalitions and help them compete with other coalitions toward entering "consciousness".

EM: Emotional codelets observe the WM's content, trying to detect and instil energy to codelets believed to require it and attach a corresponding emotional tag. As a result, emotions influence which information comes to consciousness, and modulate what will be explicitly memorized.

Step 5: The selected coalition is broadcast: The Attention mechanism spots the most energetic coalition in WM and submits it to the "access consciousness," which broadcasts it to the whole system. With this broadcast, any subsystem (appropriate module or team of codelets) that recognizes the information may react to it.

PH: PH retrieves the frequently reappearing past information that best matches the current information resident in WM, which may now contain behaviour sequences. It then extracts frequent (partial or complete) sequences of events (episodic patterns) from the sequences of events previously consolidated (see below for an explanation of the consolidation process). This may invoke a stream of behaviours related to the current event, with activation passing through the links between them. This invoked stream of behaviours could be considered as a partial or complete action procedure.

Steps 6 and 7: Here unconscious behavioural resources (action selection) are recruited: Among the modules that react to broadcasts is the Behaviour Network (BN). BN plans actions and, by an emergent selection process, decides upon the most appropriate act to adopt. The selected Behaviour then sends away the behaviour codelets linked to it.

EM: In this step when the BN starts a deliberation, for instance to build a plan, the plan is emotionally evaluated as it is built, the emotions playing a role in the selection of the steps. If the looping concerns the evaluation of a hypothesis, it gives it an emotional evaluation, perhaps from learned lessons from past experiences.

PH: Before the addition of EPL to CELTS, only the Behaviour Network (BN) inspired from Maes' BN (1989) could plan and execute actions as well as monitor frequent partial or complete sequences of events. As we have seen here, in our revised CELTS model, the PH can now also do this, and does it better.

Step 8: Action execution: Motor codelets stimulate the appropriate muscles or internal processes.

EM: Emotions influence the execution, for instance in the speed and the amplitude of the movements.

As explained in chapter II, two models are suggested in neuroscience for the consolidation phase (Purves et al., 2008), (1) the standard consolidation theory and (2) the multiple-trace theory.

We base our work on the multiple-trace theory which holds a hippocampus-dependent view of event encoding. According to this theory, every time an event causes memory reactivation, a new trace for the activated memory is created in the hippocampus. Memory consolidation occurs through the reoccurrence of loops of episodic memory traces in the hippocampus, which causes the construction of semantic memory traces in the cortex. Thus, the cortical neurons continue to rely on the hippocampus throughout encoding. Three information processes seem essential to episodic memory: the initial categorization of information coming from the senses, the association and direct storage of categorized information, and the use of this stored categorized information to build a better categorical structure for future processing of signals from the senses.

In the next two sections we explain in detail how the episodic memory consolidation and episodic learning processes are implemented in CELTS' architecture.

5.2.2 The Memory Consolidation Process

CELTS' memory consolidation process, which corresponds to McClelland (McClelland et al., 1995) memory consolidation in cortex, occurs in Step 2 of CELTS' cognitive cycle. It takes place during each of CELTS' cognitive cycles. Like the human cortex, CELTS' Episodic Learning Mechanism (EPL) extracts frequently occurring sequences from its past experience, as they were recorded in its hippocampus (PH). In our context, CELTS learns during training sessions for arm manipulation by astronauts in the *CanadarmTutor* virtual world (Nkambou et al., 2005) (Figure 4.3).

Given that an episodic trace or sequence of events is recorded during *consciousness* broadcast in CELTS, we chose the sequential pattern mining algorithm of (Fournier-Viger et al., 2008) to mine frequent event sequences. The algorithm provides several more features than the original GSP sequential pattern algorithm (Agrawal and Srikant, 1995), such as accepting symbols with numeric values, eliminating redundancy and handling time constraints. The algorithm takes the database D of all saved sequences of events as input. Here, a sequence of events is recorded for each execution of CELTS. An event $X = (i_1, i_2, \ldots i_n)$ contains a set of items $i_1, i_2, \ldots i_n$, and represents one cognitive cycle. For each event, (1) an item represents the coalition of information codelets that was broadcasted during the cognitive cycle, (2) an optional item with a numeric value indicates one of the four emotional valences in CELTS (high threat, medium fear, low threat) that are associated with the broadcasted coalition, and (3) a final optional item that represents the executed behaviour, if one was executed during that cycle. Formally, an event sequence is denoted $s = < (t_1,X_1), (t_2,X_2),\ldots, (t_n,X_n)>$, where each event X_k is annotated with a timestamp t_k indicating the cognitive cycle number. The algorithm extracts partial or complete sequences of events that occur in the database more than a minimal number of times defined by the user (*minsup*).

ID	Events sequences
S1	<(0, *c1 e1*{-0.8}), (1, *c2 e2*{-0.3} *b1*), (2, *c4 b5*)>
S2	<(0, *c1 e1*{-0.8}), (1, *c3*), (2, *c4 b4*), (3, *c5 b3*)>
S3	<(0, *c2 e2*{-0.3}), (1, *c3*), (2, *c4*), (3, *c5 b3*)>
S4	<(0, *c3*), (1, *c1 e1*{-0.6} *b4*),(2, *c3*)>
S5	<(0, *c4 b4*), (1, *c5*), (2, *c6*)>
S6	<(1, *c1 e1*{-0.6} *b4*), (2, *c4 b4*), (3, *c5*)>

Table 5.1 A Data Set of 6 Sequences

Table 5.1 shows an example of a database produced by user manipulation of Canadarm2 in the virtual world. We chose two short sequences in this example. The first event of sequence *S1* shows that during cognitive cycle 0, due to arm manipulation by the astronaut, coalition *c1* was broadcasted and that an emotional valence of -0.8 for emotion *e1* (high threat) was associated with the broadcast. The second event of *S1* indicates that at cognitive cycle 1, coalition *c2* was broadcasted with emotional valence -0.3 for emotion *e2* (medium fear) and that behaviour b1 was executed. Table 5.2 shows some sequences obtained from the application of the algorithm on the database of Table 5.1 with a *minsup* of 32 % (2 sequences) and no time constraints. The first frequent pattern is < (0, *c1 e1* {-0.7}), (2, *c4*)>, which was found in sequences *S1*, *S2*, *S4* and *S6*. Because the events containing *e1* in these sequences have numeric values -0.8, -0.8, -0.6 and -0.6, the algorithm calculated the average when extracting that pattern, which resulted in the first event having e1 with value {-0.7}. Because this pattern has a support of 66 % (4 out of 6 sequences), which is higher than *minsup*, it is deemed frequent.

Mined sequences	**Support**
<(0, *c1 e1*{-0.7}), (2, *c4*)>	66 %
<(0, *c3*), (2, *c5 b3*)>	33 %
<(0, *c4 b4*), (1, *c5*)>	50 %
<(1, *c3*), (2, *c4*), (3, *c5 b3*)>	33 %
...	...

Table 5.2 Example of Events Sequences Extracted

5.2.3 Learning Extracted Patterns

The second phase of Episodic learning, which happens in **Step 5** of CELTS' cognitive cycle, consists of mining frequent patterns from the sequences of events recorded for all executions of CELTS by applying our sequential pattern mining algorithm. This process is executed at the end of each CELTS execution.

5.2.4 Using Mined Patterns to Improve CELTS' Behaviour

The third part of Episodic learning, which happens in **Step 7** of CELTS' cognitive cycle, consists of improving CELTS' behaviour by making it reuse relevant patterns that carry a positive emotional valence. This is done by intervening in the coalition selection phase of CELTS. The idea is here to find, during each cognitive cycle, the patterns that are similar to CELTS' current execution in order to select the next coalition to be broadcasted. This coalition is the one that is estimated to be the most probable of generating positive emotions for CELTS according to these patterns. Influencing the coalitions that are broadcasted will then directly influence the actions to be taken by CELTS' Behaviour Network (BN). This allows this augmented version of CELTS to adapt itself to its environment better than the previous version. This modification of CELTS can be implemented in different ways. We used the *SelectCoalition* algorithm (Figure 5.1), which takes as parameters: (1) the sequence of previous CELTS broadcasts (*Broadcasts*), (2) the set of frequent patterns (*Patterns*) and (3) the set of coalitions that are candidates to be broadcasted during a given cognitive cycle (*CandidateCoalitions*).

This algorithm first resets a variable min and a variable max for each coalition in *CandidateCoalitions*. Then, the algorithm repeats the following four steps for each pattern p of *Patterns*. First, it computes the *strength* of p by multiplying the sum of the emotional valences associated with the broadcasts in p with the support of p (the percentage of sequences in which the pattern appeared). Then, it finds all the coalitions $c \in$ *CandidateCoalitions* that appear in p after the last k broadcast sequence of *Broadcasts* for any $k \geq 2$. For each such coalition c , if the strength of p is higher than $c.max$, $c.max$ is set to that new value. If that strength is lower than $c.min$, $c.min$ is set to that new value. Finally, when the algorithm finishes iterating the set of patterns, the algorithm returns to CELTS' Working memory the coalition c in *CandidateCoalitions* that as the highest positive value for the sum $c.min + c.max$ where $c.max > 0$. This coalition will be the one to be broadcast next by the *Attention Mechanism* (AM). In the case where no coalition meets these criteria, the algorithm will return the coalition from *CandidateCoalitions* that is the most active to CELTS' Working memory.

```
Algorithm 1 (SelectCoalition Algorithm)
SelectCoalition(Patterns, Broadcasts, CandidateCoalitions)
  FOR each Coalition c ∈ CandidateCoalitions
      c.min := 0. c.max := 0.
  FOR each pattern P of Patterns.
      Strength := CalculateSumOfEmotionalValences(P) * Support(P).
      FOR k := 2 to |P|.
          Sa := last k Broadcasts of Broadcasts.
          IF (Sa ⊆ P)
             FOR each coalition c ∈ CandidateCoalitions appearing
                    after Sa in P
                 c.max := maxOf(Strength, c.max).
                 c.min := minOf(Strength, c.min).
  RETURN c ∈ CandidateCoalitions with the largest positive
           (c.max + c.min) and such that c.max > 0.
```

Figure 5.1 CELTS' Episodic Learning coalition selection algorithm

The $c.max > 0$ criterion is included to ensure that the selected coalition appears in at least one pattern having a positive sum of emotional valences. Moreover, we have added the $c.min + c.max$ criterion to decrease the probability that coalitions appearing in patterns with a negative sum of emotional valences be selected. In our experiments, this criterion proved to be very important for it can make CELTS quickly stop selecting a coalition occurring in a positive pattern, if the coalition comes to appear in negative patterns. The reader should note that we presented here an algorithm that uses patterns which fit our needs with CELTS. However, algorithms relying on other criteria could also be used.

5.3 EVALUATION AND RESULTS

We predict that if CELTS is equipped with both EPL and EM, it will better user-adapted solutions. For instance, given a camera adjustment problem in the virtual world, an expert may define many scenarios in CELTS' BN to help a user solve the problem (Figure 5.3). Each scenario involves the activation of certain Nodes. Nodes, as explained in chapter III (see CTS' BN), contain a hint, in the form of a statement or a question. Users see these at each CELTS-user interaction. EM assigns a positive or negative valence to each interaction, according to the user's answer to the questions. Thus, given a problem in the virtual world, and after several user-CELTS interactions, EPL finds the scenario in which it has gained the highest emotional positive valence. The collaboration between EPL and EM also bring CELTS to a self-satisfaction[17] state.

Figure 5.2 represents this integrated CELTS with the Canadarm2 simulator. We also added the EPL Viewer to CELTS in order to observe CELTS' EPL behaviour, (Figure 5.2.B). Figure 5.2.C represents CELTS' interaction with the user.

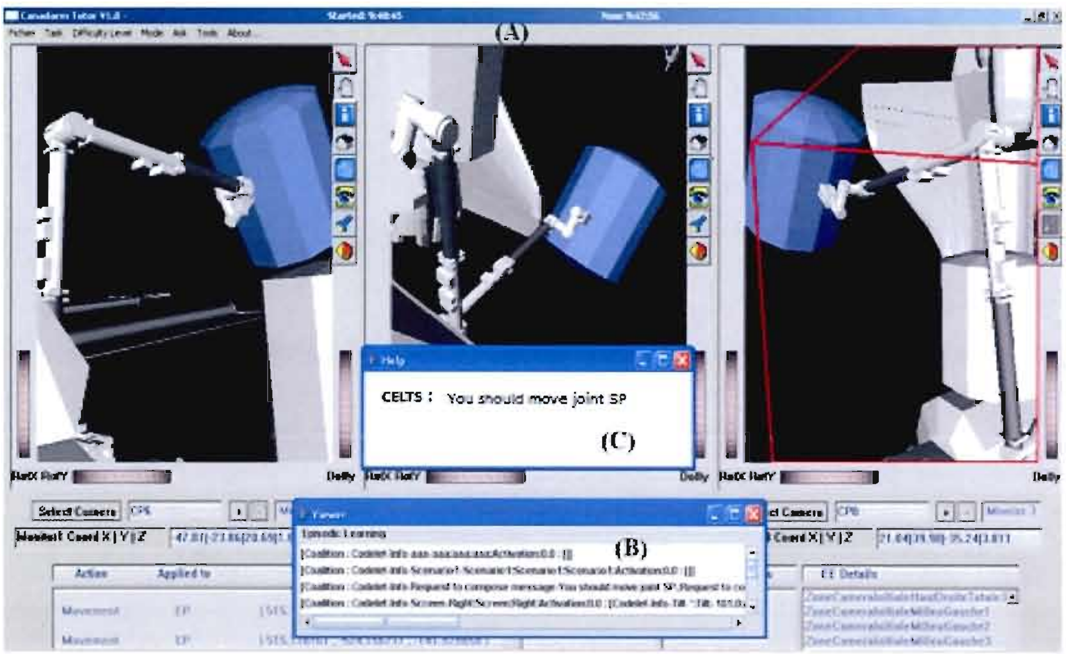

Figure 5.2 (A) Simulator interface (B) Episodic Learning Viewer (C) CELTS Intervention

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[17]Self-satisfaction:"*a usually smug satisfaction with oneself or one's position or achievements*." (Merriam-Webster, 2010)

5.3.1 Users' Learning Situations

A user learns by practicing arm manipulations and receiving hints created initially by an expert and communicated to the user by CELTS. The learner's success (defined as the extent of self-satisfaction in CELTS) will be variable, depending on CELTS' appropriate application of these hints.

We performed 250 CTS executions of Canadarm2 in *CanadarmTutor* for a camera adjustment problem in which experts defined different scenarios in CELTS' BN (Figure 5.3). During each execution, CELTS chooses a scenario based on the situation. CELTS' EPL creates a trace for each execution. These traces contain all the information transferred from CELTS to the users and back. After each CELTS execution, EPL extracts frequent patterns and the emotional valences attributed to the given scenario, and use these for future interactions. Our experiments showed that the users manipulating Canadarm2 tend to better react to a problem when having received hints from CELTS prior to receiving the actual solution.

When the user's actions lead to a problematic situation, CELTS provide assistance in one of two ways. It can either give a direct solution to the user, or decide to give hints to the user prior to giving him the actual solution. To illustrate these two possibilities for a given situation, we here take the example of a camera adjustment situation in which CELTS must react.

It is a fact that users must perform camera adjustments before moving the Arm in the virtual world. During our experiments, we noted that users frequently forgot this step, and moreover, users frequently did not realize that they had neglected this step. This increases the risk of collisions (as depicted in Figure 5.2.A) in the virtual world. We thus decided to implement this situation as a *medium-threat* situation in CELTS' BN (see Figure 5.3).

When a user forgot to perform camera adjustments, CELTS had to make a decision; it could either (1) give a direct solution such as "You must stop the arm immediately" (scenario 1, Figure 5.3) or (2) give a brief hint such as "I think this movement may cause some problems. Am I wrong or right?" (scenario2, Figure 5.3) or (3) give a proposition such as "Stop moving the arm and revise your lessons". Through interactions with different users, EPL recorded sequences of events, each of them carrying emotional valences. The average length of the stored sequences was of 26 CELTS-events.

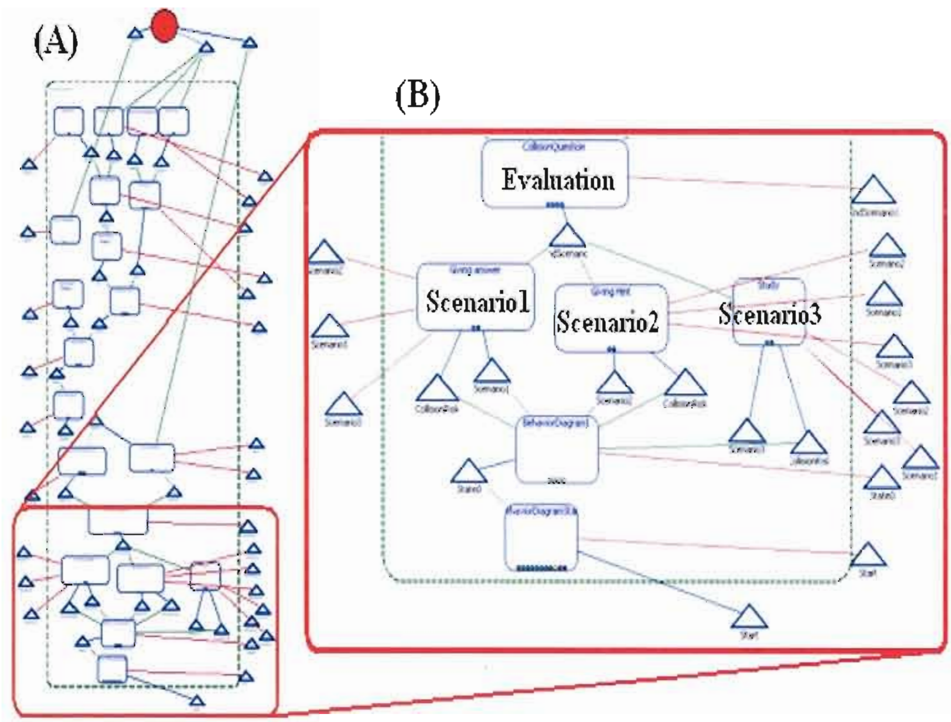

Figure 5.3 Part of the CELTS Behavior Network

During CELTS' coalition selection phase (Step 4 and 5 of CELTS' cognitive cycle), the learning mechanism evaluates all mined patterns to detect all patterns similar to its current execution that have resulted in self-satisfaction or dissatisfaction. In order to give a brief description of both scenarios, in our present case concerning Camera adjustment, we mined all the patterns concerning scenario 1(direct solution), scenario 2 (hint given first) and scenario 3 (proposition).

Scenario 1

CELTS' EPL detected that CELTS' EM attributed *negative* valences to this scenario. The following sequence is an example of the sequences extracted by the data mining algorithm: <(*t*=0, *c1*), (*t*=1, *c2*),(*t*=2, *c3*),(*t*=3, *c4*),(*t*=4, *c5*), *e*{-0.9}>. It must be noted that we here show the mean emotional valence for this sequence; the emotional valences given by EM to each event (in each step) in the sequence are not shown. The sequence contains the following information: at time 0, the broadcast coalition c1 indicates that a collision risk was imminent in the virtual world; at time 1, the broadcasted coalition *c2* indicates that CELTS gave the answer to the user; at time 2, the broadcasted coalition *c3* indicates that the user did not know why there was an imminent collision risk; at time 3, the broadcasted coalition c4 indicates that CELTS gave a hint to the user; at time 4, the broadcasted coalition c5 indicates that scenario1 received an emotional valence equal to -0.9 from CELTS' EM due to the user's answers.

Importantly, in this scenario, users received direct solutions from CELTS, but nonetheless failed to react properly. This failure thus led CELTS' EM to associate the negative valence -0.9 to the emotion e1 (medium fear). The conclusion is that this scenario is not a good candidate for the collision risk problem.

Scenario 2

CELTS' EPL detected that CELTS' EM attributed *positive* valences to this scenario. The following sequence is an example of those extracted by the data mining algorithm: <(*t*=14,*c2*),(*t*=15,*c21*),(*t*=16,*c22*),(*t*=17,*c23*), *e2* {0.7}>. Again, It must be noted that we here show the mean emotional valence for this sequence; the emotional valences given by EM to each event (in each step) in the sequence are not shown. The scenario 2 contains the following information: at time 14, the broadcasted coalition *c2* indicates that a collision risk was imminent in the virtual world; at time 15, the broadcasted coalition *c21* indicates *give a hint*; at time 16, broadcasted coalition *c22* indicates *give the answer;* and at time 17, broadcasted coalition *c23* indicates that the user's reaction was correct. As a result, CELTS' EM attributed a positive emotional valence of 0.7 to the sequence as a whole. Given these positive emotional valences, we conclude that the best solution for Camera adjustment problems is CELTS giving a hint (Figure 5.3 scenario 2).

Scenario 3

CELTS' Episodic Learning Mechanism detected that CELTS' EM attributed zero emotional valence to this scenario. The following sequence is an example of those extracted by the mined algorithms: < (*t*=44, *c2*), (*t*=45, *c51*), (*t*=46, *c52*), (*t*=47, *c53*), *e* {0} >. Again, it must be noted that we here show the mean emotional valence for this sequence; the emotional valences given by EM to each event (in each step) in the sequence are not shown. Scenario 3 contains the following information: at time 44, the broadcasted coalition *c2* indicates that a collision risk was imminent in the virtual; at time 45, the broadcasted coalition *c51* indicates following message *please revise your course*; at time 46, the broadcasted coalition *c52* indicates *user is inactive;* and at time 47, the broadcasted coalition *c53* indicates that the user decided to stop software. As a result, CELTS' EM has attributed a zero emotional valence to the sequence as a whole. Given the zero emotional valence, we conclude that this scenario is not appreciated by most users. The conclusion is that this scenario is not a good candidate for the collision risk problem.

Episodic learning in CELTS continuously seeks the sequences with the most positive emotional valences and highest frequencies. In our example, the event (*t*=14, *c2*), (*t*=15, *c21*) met these requirements. In future cases, if the emotional valence is not as positive as was the case in our example, CELTS may choose another scenario rather than scenario2. It should be noted that because the set of patterns is regenerated after each CELTS execution, some new patterns can emerge, while others can disappear, depending on the new sequences of events stored by CELTS. This ensures that CELTS' behaviour can change over time in the case that some scenarios become less or more negative and also, more generally, that CELTS can adapt its behaviour to a dynamic environment.

To regulate learning rate and scenario selection, CELTS' EPL performs the following: 1) for any new situation, CELTS randomly selects one among all of the possible BN scenarios conceived by the expert (Figure 5.3) in order to solve the problem. It must be noted that regardless of the ongoing process at any given time (learning or unlearning), the random function choice of scenarios always remains active; 2) As explained in this chapter, scenarios are attributed positive or negative emotional valences at the end of each execution; 3) Lastly, EPL learns new scenarios at the learning rate assigned by an expert. The learning rate is adjustable according to the *minsup* as detailed in the previous section. In our case it is set at six executions (learning rate is 5%) (Figure 5.4.B). It is sometimes the case that a previously successfully accomplished scenario for a given situation is not well understood by another user. The valence for this scenario then goes from positive to negative. In these cases, EPL will switch to other scenarios in an attempt to return to a successful behaviour in the given situation. Once the user again successfully accomplishes one of these new scenarios, EPL will attribute a positive valence to this new scenario, and learning will have again occurred.

This process is illustrated in Figure 5.4. From execution zero to three, while EPL learns scenario1, CELTS continued to choose scenarios randomly. At executions 4 and 6, EPL intervened and chose scenario1.

From execution 7 to 10, CELTS again randomly chose scenarios. There was no EPL intervention in scenario selections. Once learning for scenario1 was completed, the user had still not answered the scenario1's questions (Figure 5.4.A) correctly. The learning rate thus went down to five percent for the subsequent executions of that scenario- the scenario was unlearned.

However, during the unlearning phase of scenario1 (Figure 5.4.A), from execution 10 to 16, both scenario1 and scenario2 were chosen. This is due to CELTS' random function and EPL's choices- execution of scenario1 and scenario2. At execution 15, the user answered scenario2's questions correctly. Thus EPL started to intervene in the scenario selection process by choosing scenario2. As demonstrated in Figure 5.4.A, during EPL's scenario2 learning phase, scenario3 was also chosen, again originating from CELTS' random scenario selection function. It must be noted that during executions, scenario3's question were always answered incorrectly by user- this is why EPL learned that scenario3 is irrelevant to the situation. Finally, when the learning for scenario1 was complete (Figure 5.4.A cycle twenty one), and the user had still not answered questions incorrectly, the learning rate stopped changing. From this point forward, CELTS most often chose scenario2 for interactions with the user. However, there remained a random selection for other scenarios for the other executions. This would continue until the user answers the scenario2 questions incorrectly, and correctly answers another scenario's questions.

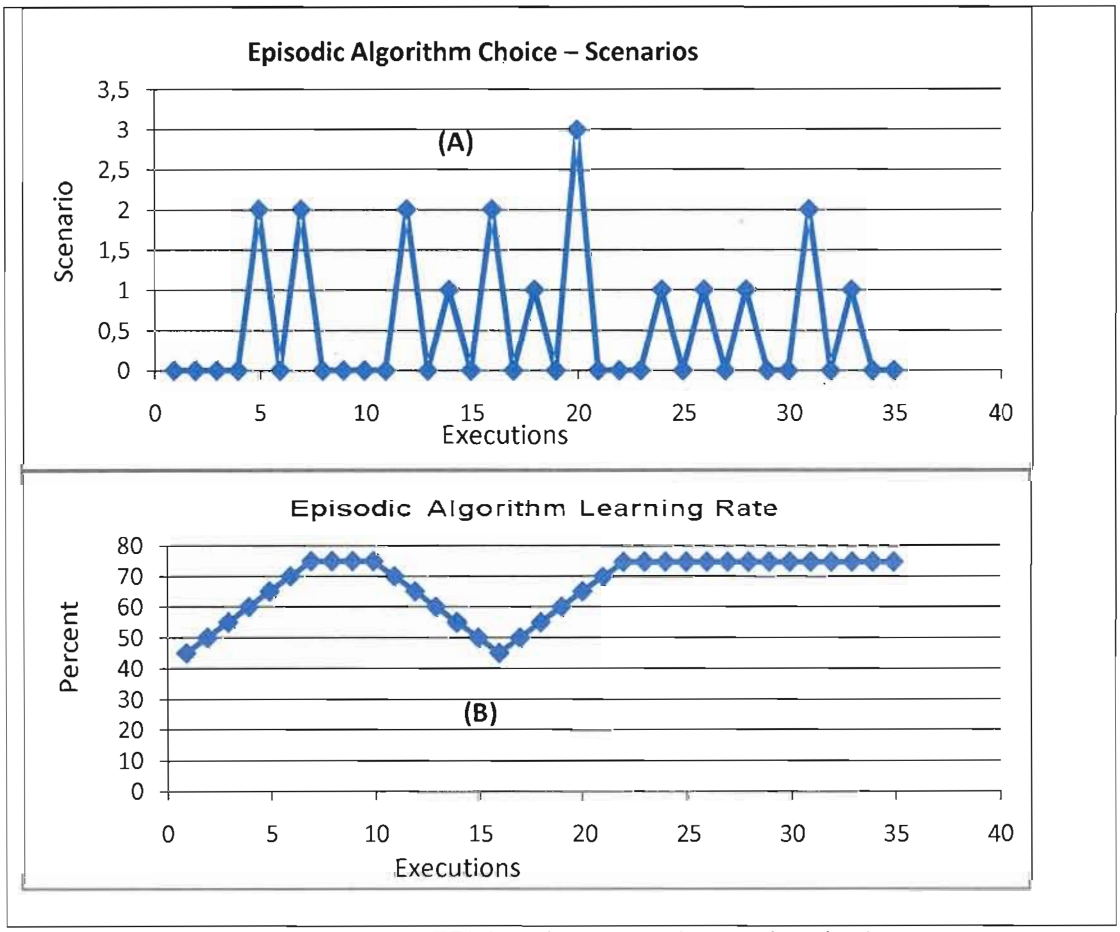

Figure 5.4 EPL learning rate and scenario selections

Using this information, the learning mechanisms has shown to be beneficial for it allows CELTS to adapt its actions to learners by choosing between different scenarios based on its previous experience. This feature is very useful in the context of a cognitive agent, as it allows the designers to include much alternative behaviour but to let CELTS learn by itself which ones are the most successful.

5.3.2 How Episodic and Emotional Mechanisms Collaborate

We now explain how emotional interventions influence CELTS' Episodic Learning Mechanism and decision making when it is faced with various situations. We performed a number of experiments with and without Emotional interventions in various situations. At the end of each experience, data mining algorithms extracted the useful patterns contained in these scenarios, which CELTS will then use to improve its reactions in future user interactions. The Emotional interventions thus influence CELTS' broadcast mechanism. They also influence the mean energy of CELTS' BN when a specific (desired or undesired) situation is observed in the virtual-world while CELTS interacts with users.

Figure 5.5 presents the energy reaction of both the BN (the first and third graphs) and the Emotional Mechanism (second graph) of CELTS when it faces a collision risk. The first graph shows the mean energy of CELTS' BN while interacting with a user. As we can see, energy levels range from 8 to 9.50, which is not considered to be a significant variation. This tells us that the mean energy of CELTS' BN does not vary significantly when there are no emotions triggered by the inputs from the virtual world. As mentioned above, the information is registered as a sequence following each scenario's execution. For each action executed by BN, a node (e.g. (0, *c8*})) is added to the corresponding sequence. Thus, each interaction with a user (node in a sequence) receives an emotional valence from the EM.

For our first experiment, we sought to test the effect of the deactivating CELTS' Emotional Mechanism on its reaction to threats. For example, the sequence $<(t=0, c8), (t=1, c9), (t=2, c10), (t=3, c11)>$ contains the following information: at time zero coalition *c8* indicates a collision risk in the virtual world and this is broadcasted back to the system. The second node (*an event*) in the sequence (*t*=1, *c9*) indicates that at time 1, the coalition *c9* was broadcasted to the system. The message *give a hint* is transferred to the user. By giving this hint, CELTS tells the user that this is a dangerous situation and that the user must react immediately. The third event (*t*=2, *c10*) indicates that at time 2, coalition *c10* is broadcasted to the system sending the message that the user's reaction is incorrect.

We can thus note that despite the sequence's danger warning, CELTS did not show significant variation of energy; it did not react intensely to the situation, as it should have.

In our second experiment, using the same situation as before, we now activated CELTS' EM. For each action executed by the BN, we added the emotional valence *e* {-1}. Thus, the sequence used in the first example became <(*t*=0,*c8*}) , (*t*=1,*c9*) , (*t*=2,*c10*) , (*t*=3,*c11*) , *e*{-1} >. This modified sequence contains the following information: at time 0, coalition *c8* indicates that a collision risk in the virtual world was broadcasted in the system. The emotional valence given by EM equals -0.9, as indicated by *e* {-0.9}. CELTS' EM interpreted the information received from the environment as a very dangerous (high-threat) situation. At time 1, (*t*=1, *c9*), *e* {-1} indicates that the coalition c9 was broadcasted and that a *message containing a hint* was sent to the user. This event received the emotional valence (-1) because the situation was deemed very dangerous. At time 2, (*t*=2, *c10* *e* {-1}) indicates that the coalition c10 was broadcasted in the system; the user's answer was incorrect. At this point the user had to receive an appropriate answer to fix the catastrophic situation made in the virtual world as soon as possible. At time 3, ((*t*=3, *c11*), *e* {-1}) indicates that the coalition *c11* sent a message containing the answer to the user. Regardless of the user's performance, it can be noted that in this experiment with the Emotional Mechanism activated, CELTS was able to react appropriately to the high-threat situation. Indeed, the second graph shows the Emotional Mechanism reactions in this second setting. We see that now, four very negative reactions received approximately a -1 valence. This negative energy is sent back directly to CELTS' broadcast mechanism. The Emotional intervention excites other modules such as the Attention Mechanism and all other CELTS' modules in order to increase the intensity of the reaction and avoid the threat with rapidity. During the execution depicted in the third graph, we can see that after the consciousness mechanism has broadcasted the information through the system, and the deliberation phase is completed, a decision is made (steps 6, 7 of cognitive cycle). If the broadcasted information is assigned an emotional valence immediately, a behaviour is set-off by CELTS' BN. Thus, the emotional negative energy boosts the intensity of the BN while executing behaviour.Comparing the first and third graph in Figure 5.5, our experiments are consistent with human decision making processes. This result of the deactivated CELTS' EM can be related to Phelps' observations of individuals with lesions to the amygdala. Such patients, although consciously aware of a threat, do not react to it with the emotional intensity of healthy individuals (e.g. increase heart beat, sweating, etc.) (Phelps, 2006).

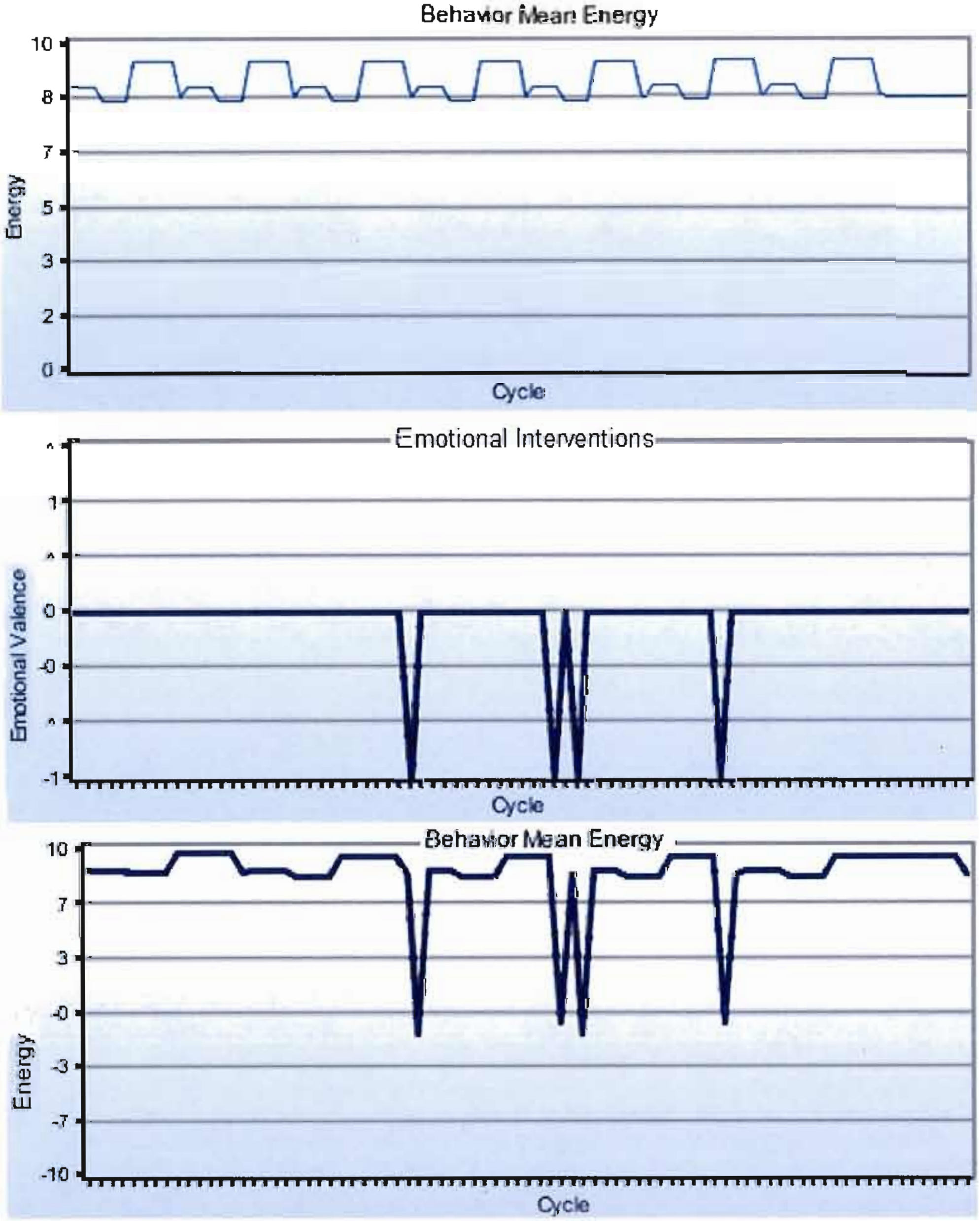

Figure 5.5 Results from emotional interactions

5.4 CONCLUSION

In this chapter, using a sequential pattern mining approach, we described how to implement an Episodic Memory and Episodic Learning Mechanism in CELTS. The interaction between an agent and its dynamic environment generates large amounts of data. The sequential pattern mining approach is proven very useful to extract significant information from the huge amount data that they have to handle. The episodic learning algorithm used in this work is inspired from a memory consolidation theory which is biologically plausible. The collaboration between the Emotional Mechanism and this Episodic Learning helps to choose the behaviours that are most likely to bring the agent to a self-satisfactory emotional state. In the next chapter we will explain how to use the sequential pattern mining algorithms with association rules to implement causal learning in CELTS.

CHAPTER VI

IMPLEMENTATION OF CAUSAL LEARNING IN CELTS

In the previous chapter, we showed that our model of declarative episodic memory improves in some respects on McClelland et al.'s 1995 model (for instance by improving on the recall part of their model); in this chapter, we improve the model of cortical declarative memory by adding causal memory and learning to the model.

One of CTS' most significant limitations is its incapacity to find out why an astronaut has made a mistake, i.e., to find the causes of the mistakes. To address this issue, we propose to integrate a Causal Learning Mechanism within CELTS and to combine it with its existing Emotional Learning Mechanism. The goal is to propose a causal model that can find associative or causal relations between events occurring in CELTS' cognitive process.

In humans, the process of inductive reasoning stems in part from activity in the left prefrontal cortex and the amygdala; it is a multimodular process (Goel and Dolan, 2004). We base our proposed improvements to CELTS' architecture on this same logic.

Researchers in causality are interested in finding the relation between cause and effect. Causal learning is the process through which we come to infer and memorize an event's reasons or causes based on previous beliefs and current experience that either confirm or invalidate previous beliefs (Maldonado et al., 2007). Human beings systematically construct their causal knowledge based on episodic memory. Given that episodic memory contains the memory of the outcomes of events , we make inductive abstractions to construct relations between events. Thus, in humans, causal memory is influenced by the information retained by episodic memory. Inversely, new experiences are influenced by causal memory (Martin and Deutscher, 1966, Shoemaker, 1970, Perner, 2000, Bernecker, 2008). In the context of CELTS, we refer to Causal Learning as the use of inductive reasoning to generalize rules from sets of experiences. CELTS observes users' behaviour without complete information regarding the reasons for their behaviour. Our prediction is that, through inductive reasoning, it will be capable of inferring the best set of causal relations from its observations of users' behaviour.

The goal of CELTS' Causal Learning Mechanism (CLM) is two-fold: 1) to find causal relations between events during training sessions in order to better assist users; 2) to implement partial procedural learning in CELTS' Behaviour Network.

To implement CELTS' CLM, we draw from Maldonado's work (Maldonado et al., 2007), which defines three hierarchical levels of causal learning: 1) the lower level, responsible for the memorization of task execution; 2) the middle level, responsible for the computation of retrieved information; 3) the higher level, responsible for the integration of this evidence with previous causal knowledge.

6.1 CAUSAL LEARNING MODELS AND THEIR IMPLEMENTATION IN COGNITIVE AGENTS

To our knowledge, two research groups have attempted to incorporate Causal Learning mechanisms in their cognitive architecture. The first is Schoppek with the ACT-R architecture (Anderson, 1993), who hasn't included a role for emotions in this causal learning and retrieval processes. ACT-R constructs the majority of its information according to the I/O knowledge base method. It also uses a sub-symbolic form of knowledge to produce associations between events. As explained by Schoppek (2002), in ACT-R, sub-symbolic knowledge applies its influence through activation processes that are inaccessible to production rules.

However, the causal model created by Schoppek in ACT-R "overestimates discrimination between old and new states". The second is Sun (2006) who proposed the CLARION architecture. In CLARION's current version, during bottom-up learning, the propositions (premises and actions) are already present in top level (explicit) modules before the learning process starts, and only the links between these nodes emerges from the implicit level (rules). Thus, there is no unsupervised causal learning for the new rules created in CLARION (Hélie, 2007). Various causal learning models have been proposed, such as Gopnik's model (2004). All proposed model use a Bayesian approach for the construction of knowledge. Bayesian networks work with hidden and non-hidden data and learn with little data. However, Bayesian learning need experts to assign predefined values to variables (Braun et al., 2003). Another problem for Bayesian learning, crucial in the present context, is the risk for combinatory explosion in the case of large amount of data. In our case, constant interaction with learners creates the large amount of data stored in CELTS' modules, For this last reason, we believe that a combination of sequential pattern mining algorithms with association rules is more appropriate to implement a causal learning mechanism in CELTS. The other advantage of causal learning using theusing the combination of AR and SPM is that the systemCELTS can then learns in a real-time incremental manner – i.e.that is, the system can update its information by interacting with various users. A final reason for choosing association rules is that the aforementioned problem explained by Schoppek, which occurs with ACT-R, cannot occur when using association rules for causal learning. However, it must be noted that although data mining algorithms learn faster than Bayesian networks when all data is available, they have problem with hidden data. Furthermore, like Bayesian learning, there is a need for experts, since the rules found by data mining algorithms must be verified by a domain expert (Braun et al., 2003). In the next section, we describe in detail our approach to causal learning and put forward its advantages and limits.

6.2 CAUSAL MEMORY AND CAUSAL LEARNING IN CELTS' ARCHITECTURE

CELTS' Causal Learning takes place during its cognitive cycles. CELTS' WM is monitored by expectation codelets and other types of codelets (see CELTS' Emotional Mechanism for more details (Faghihi et al., 2009b)). If expectation codelets observe information coming in WM confirming that the behaviour's expected result failed, then the failure brings CELTS' Emotional and Attention mechanisms back to that information. To deal with the failure, emotional codelets that monitor WM first send a portion of emotional valences sufficient to get CELTS' attention to select information about the failed result and bring it back to consciousness. The influence of emotional codelets at this point remains for the next cognitive cycles, until CELTS finds a solution or has no remedy for the failure. Since, relevant resources need to be recruited, to allow CELTS' modules to analyze the cause of the failure and to allow deliberation to take place concerning supplementary and/or alternative actions, the consciousness mechanism broadcasts this information to all modules. Among different modules inspecting the broadcasted information by the consciousness mechanism, the Episodic and Causal Learning mechanisms are also collaborating to find previous sequences of events from Long Term Memory (LTM) content that occurred before the failure of the action. These sequences of events are the interactions that took place between CELTS and users during Canadarm2 manipulation by users in the virtual world. They are saved to different CELTS' Memories respecting the temporal ordering of the events that occurred between users and CELTS. The retrieved sequences of events contain the nodes (Figure 6.3.D). Each node contains at least an event and an occurrence time (see CELTS' Episodic Learning (Faghihi et al., 2009b) for more information). For instance, in Figure 6.3.D, different interactions may occur between users and CELTS depending on whether the nodes' preconditions in the Behavior Network (BN) become true. To find the causes of the problem produced by the users in the virtual world, the CLM constantly extracts association rules (e.g. X→Y) between sets of events with their confidence and support[18] (Agrawal et al., 1993) from all past events. From these associations, CLM then eliminates the rules that do not meet a minimum confidence and support according to the temporal ordering of events, within a given time interval. This eliminates the non-causal rules from the LTM' retrieved sequences of events. After finding the candidate rule as the cause of the failure, CELTS' CLM re-executes it and waits for the user feedback. However, if after the execution of the candidate rule it turns out that it did not help the user to solve the problem, then CELTS' CLM writes in a failure in the WM. The failure leads CELTS' Causal Learning to examine other related nodes to the current failure with the highest support and confidence. Each time a new node is proposed by Causal Learning and executed by BN, an expectation node brings back to the consciousness mechanism the confirmation from users to make sure that the found rule is the cause of the failure. Finally, if a new cause is found, it will be integrated in CELTS' Causal Memory. In the end, if no solution can be found, the Causal Learning Mechanism puts the following message in WM: "I have no solution for this problem".

After having proposed our causal model for CELTS, we now explain in detail the intervention of the causal process in CELTS' cognitive cycles. It is important to remember that two routes are possible during CELTS' cognitive cycle- a short route[19] (no causal learning occurs in this route) and a long route (various types of learning occur in this route such as episodic, causal and procedural). In both cases, the cycle begins with the perceptual mechanism. Hereafter, we briefly summarize each step in

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[18] Given a transaction database D is defined as a set of transactions $T=\{t1,t2...tn\}$ and a set of items $I=\{i1, i2,...in\}$, where $t1,t2,...,tn \subseteq I$. The support of an itemset $X \subseteq I$ for a database is denoted as sup(X) and is calculated as the number of transactions that contains X. The support of a rule $X \Rightarrow Y$ is defined as $sup(X \cup Y) / |T|$. The confidence of a rule is defined as $conf(X \Rightarrow Y) = sup(X \cup Y) / sup(X)$.

[19] The short route is a percept-reaction direct process, which takes place when the information received by the perceptual mechanism is strongly evaluated by the pseudo-amygdala. The short route is described elsewhere. The long route is CELTS' full cognitive cycle. (Faghihi et al., 2008).

the cycle and in italics, describe the influence of emotions (here called pseudo-amygdala[20] or EM and/or of CLM).

Step 1: The first stage of the cognitive cycle is to perceive the environment; that is, to recognize and interpret the stimulus (see (Dubois et al., 2007) for more information).

EM: All incoming information is evaluated by the Emotional Mechanism when low-level features recognized by the perceptual mechanism are relayed to the emotional codelets, which in turn feed activation to emotional nodes in the Behaviour Network (BN). Strong reactions from the "pseudo-amygdala" may cause an immediate reflex reaction in CELTS.

Step 2: The percept enters Working Memory (WM): The percept is brought into WM as a network of information codelets that covers the many aspects of the situation (see (Dubois et al., 2007) for more information).

EM : In this step, if the received information is considered important or dangerous by EM, there will be a direct reaction from EM which primes an automatic behaviour from BN (Faghihi et al., 2008b).

CLM: CLM also inspects and fetches WM information. Relevant traces from different memories are automatically retrieved, which contain codelet links with other codelets. These will be sequences of events in the form of a list relevant to the new information. The list includes the current event, its relevant rules and the residual information from previous cognitive cycles in WM. Each time new information codelets enter WM, the memory traces are updated depending on the new links created between these traces and the new information codelets. Once information is thus enriched, CLM sends it back to the WM.

---

[20] Let us note that in CELTS, a "pseudo-amygdala" is responsible for emotional reactions (Faghihi et al., 2009).

Step 3: Memories are probed and other unconscious resources contribute: All these resources react to the last few consciousness broadcasts (internal processing may take more than one single cognitive cycle).

Step 4: Coalitions assemble: In the reasoning phase, coalitions of information are formed or enriched. Attention codelets join specific coalitions and help them compete with other coalitions toward entering "consciousness".

EM: Emotional codelets observe the WM's content, trying to detect and instil energy to codelets believed to require it and attach a corresponding emotional tag. As a result, emotions influence which information comes to consciousness, and modulate what will be explicitly memorized.

Step 5: The selected coalition is broadcasted: The Attention mechanism spots the most energetic coalition in WM and submits it to the "access consciousness," which broadcasts it to the whole system. With this broadcast, any subsystem (appropriate module or team of codelets) that recognizes the information may react to it.

CLM: CLM starts by retrieving the past frequently reappearing information that best matches the current information resident in WM, ignoring their temporal part. This occurs by constantly extracting associated rules from the broadcasted information and the list of events previously consolidated. Then, CLM eliminates the rules that do not meet the temporal ordering of events.

Steps 6 and 7: Here unconscious behavioural resources (action selection) are recruited. Among the modules that react to broadcasts is the Behaviour Network (BN): BN plans actions and, by an emergent selection process, decides upon the most appropriate act to adopt. The selected Behaviour then sends away the behaviour codelets linked to it.

EM: When CELTS' BN starts a deliberation, for instance to build a plan, the plan is emotionally evaluated as it is built, the emotions playing a role in the selection of the steps. If the looping concerns the evaluation of a hypothesis, it gives it an emotional evaluation, perhaps from learned lessons from past experiences.

CLM: The extraction of the rules in step 5, may invoke a stream of behaviours related to the current event, with activation passing through the links between them Figure 6.3.D). At this point CLM wait for the CELTS' Behaviour Network and CELTS' Episodic Learning Mechanism solution for the ongoing situation) (Faghihi et al., 2009b). Then, CLM puts its proposition as a solution in CELTS' WM, if the propositions from the decision making and the episodic learning mechanisms are not energetic enough to be chosen by CELTS' Attention Mechanism.

Step 8: Action execution: Motor codelets stimulate the appropriate muscles or internal processes.

EM: Emotions influence the execution, for instance in the speed and the amplitude of the movements.

CLM: The stream of behaviours activated in the CELTS' BN (step 7) may receive inhibitory energies, from CLM, for some of their particular behaviours. This means that, according to CELTS' experiences, CLM may use a shortcut (i.e., eliminate some intermediate nodes) between two nodes in behaviour Network (BN) to achieve a goal (e.g., in Figure 6.3.D two points v and z). In some cases, again according to CELTS' experiences, CLM may prevent the execution of unnecessary behaviours in CELTS' BN during the execution of a stream of behaviours.

6.3 THE CAUSAL LEARNING PROCESS

The following subsections explain the three phases of the Causal Learning Mechanism as it is implemented in CELTS' architecture.

6.3.1 The Memory Consolidation Process

The causal memory consolidation process takes place during each CELTS's cognitive cycle (in Step 2 of CELTS' cognitive cycle), and is very similar to the Memory Consolidation Process in CELTS' Episodic Learning Mechanism (see previous chapter). Like the human left prefrontal cortex, CELTS' Causal Learning Mechanism (CLM) extracts frequently occurring events from its past experiences, as they were recorded in its different memories (Goel and Dolan, 2004). Accordingly, a trace of what occurred in the system is recorded in CELTS' various memories during consciousness broadcasts (Faghihi et al., 2009b). For instance, each event $X= (t_i,A_i)$ in CELTS represents what happened during a cognitive cycle. While the timestamp t_i of an event indicates the cognitive cycle number. The set of items A_i of an event contains an item that represents the coalition of information codelets (see step 4 of CELTS' cognitive cycle) that was broadcasted during the cognitive cycle. For example, ignoring the emotional valence attributed to the event, one partial sequence recorded during our experimentations was < (*t*=1, *c2*), (*t*=2, *c4*)>. This sequence shows that during cognitive cycle 1 the coalition *c2*, (indicating that the user forgot to adjust the camera in the simulator Figure 6.3.A) was broadcasted, followed by the broadcast of *c4* (indicating that the user caused a collision in the simulator, Figure 6.3.A during the cognitive cycle 2).

6.3.2 Learning by Extracting Rules from What Is Broadcasted in CELTS

The second phase of Causal learning, which occurs in Step 5 of CELTS' cognitive cycle, deals with mining rules from the sequences of events recorded for all of CELTS' executions. To do so, the algorithm presented in Figure 6.1 takes as input the sequence database LTM Patterns (sequences of coalitions that were broadcasted for each execution of CELTS), *minsup, minconf* and *UserTrace* which are the traces of what occurs between users and the application. CELTS' uses the first three parameters to discover the set of all causal rules (R1, R2,..., Rn) contained in the database (Step 1). It then tries to inspect rules that match with the interactions between the current user and CELTS (User_trace) in order to discover probable causes that could explain the user's behavior (Step 2). When it does, one cause is returned.. The algorithm (Figure 6.1) performs as follows. 1) In STEP1, it saves in a sequence database the sequences of nodes (the coalitions) that are broadcasted by CELTS' BN during interactions with users to solve a problem. Then, in STEP2, the algorithm uses the Apriori algorithm (Agrawal et al., 1993) for mining association rules between nodes. This uncovers association rules of the form R_i : NODE$_i$ → NODE$_f$, where NODE$_f$ and NODE$_i$ are potential causes and effects of the failure The meaning of an association rule R_i is that if NODE$_f$ appears, we are likely to also find NODE$_i$ in the same sequence. But it can be before or after. For this reason, the algorithm reads the original sequence database one more time to eliminate rules that do not respect the temporal ordering. To do this, we use minimum causal support and causal confidence thresholds that a rule should meet in order to be kept. Let *s* be the number of sequences in the sequence database. The causal support and confidence of a rule are defined respectively as sup (NODE$_i$ ■ NODE$_f$) / *s* and sup (NODE$_i$ ■ NODE$_f$) / sup (NODE$_i$), where sup(X ■ Y) denotes the number of sequences such that NODE$_i$ *appears before* (■) NODE$_f$ and sup (NODE$_i$) represents the number of sequences containing NODE$_i$ (see (Fournier-Viger et al., 2010) for more details). After eliminating the association rules that do not meet the minimum support and confidence thresholds, the set of rules that is kept is the set of all causal rules. A causal rule NODE$_i$ → NODE$_f$ is interpreted thus: if NODE$_i$ occurs, then NODE$_f$ is likely to occur thereafter. In that case we will call NODE$_i$ the cause of the failure and NODE$_f$ the effect; 2) In STEP2, CLM tries to select the more likely cause for a failure. To do so, this algorithm sets variables MaxCE to zero. It then computes the causal estimation (CE_K) for each rule by multiplying its *support and confidence.*

Causal estimation (*CE*) of R_i = (support of R_i * confidence of R_i **)**

Then, it calculates which node is the most likely to be the cause (the left part of the rule having the highest CE_K). CE_K is the causal estimation of a rule according to all the information broadcast in the system. For each such rule *r*, if the CE_K is higher than $c.max, c.max$ is set to that new value (CE_K). If the CE$_K$ is lower than MaxCE, MaxCE remains intact. Finally, when the algorithm finishes iterating over the set of rules, the algorithm returns to CELTS' working memory the node (coalition)

CandidateCoalitions contained in the left part of the rule that has the highest probability value for the $c.min + c.max$ and where $\mathrm{c.max} > 1220$. Using this method for each node of the retrieved sequence, CELTS' CLM finds the most probable causes of the problem produced by the user manipulating Canadarm2 in the virtual world. This node (coalition) will be broadcasted next by CELTS' attention mechanism to the user for further confirmation (see the next subsection for detail).

```
SelectCausalNodes (LTMPatterns, MinSupp, MinConf, UserTrace)

STEP 1:

    Find the sets of association rules AR with the Apriori algorithm for a minimum
    support and confidence thresholds.

    FOR each association rule found

        Calculate its causal support and causal confidence by looking at the
        sequence database again.

        Eliminate the rule if the causal support and causal confidence are
        lower than minimum thresholds for causal confidence and causal
        support.

    END FOR

STEP 2:

    MaxCE =0.0.

    FOR  each rule R_i  found in STEP1

            IF  R.Left ⊆ UserTrace

                    CE_K := R.causalSupport * R.causalConfidence

                    IF(CEK > MaxCE)

                     MaxCE :=  CE_K
                     CandidateCoalition.add : =  R.Right

              END IF

          END IF

    END FOR

RETURN CandidateCoalition,  MaxCE
```

Figure 6.1 Causal Learning algorithm

6.3.3 Construction of CELTS' Causal Memory

The creation of CELTS' Causal Memory (CM) occurs in steps 7 and 8 of the cognitive cycle. The main elements of Causal Memory are the rules such as $X \rightarrow Y$. Like CELTS' Behaviour Network (BN), the rules' left and right parts are nodes which are the coalitions broadcasted during CELTS' interactions with users. Each rule has a support and a confidence (see CE in previous subsection). Each new node (such as $NODE_p$) includes a context, an action, a result, and one or more causes. The context in this newly created node describes an ongoing event. The left part of the rule is filled by the node that caused the failure. The right part of the rule is considered as the effect. In what follows, we explain in detail how causal memory is formed. The algorithm is presented in Figure 6.2. It takes as parameters the sequence database LTM Patterns, which are the sequences retrieved from the Long-term Memory, the maximum causal estimated node (MaxCE) calculated in the previous section, and the $NODE_f$ which is brought about by the user's error. Given the node $NODE_f$ that caused the error after execution by CELTS' BN, CLM creates (see Figure 6.2.STEP1) an empty rule (*R*) in CELTS' CM and copies the information in $NODE_f$ into the right part of the rule. During a user's manipulation of Canadarm2, CLM finds, from the current sequence of executed nodes, the node $NODE_p$ executed prior to $NODE_f$ which caused the user's error. It then attaches an expectation codelet to node $NODE_p$, puts it into the WM to be executed by BN and waits for the user's confirmation to find the cause of the problem. If the cause of the failure is $NODE_p$, CLM copies the action of node $NODE_p$ into the cause of the node $NODE_f$. CLM then copies the information of $NODE_p$ into the left part of the created rule R in CELTS' Causal Memory and makes a direct link between $NODE_f$ and $NODE_p$.

If, however, it turns out that the node $NODE_p$ in the previous step is not the cause of the error, CLM then (Figure 6.2. STEP2) searches for the node $NODE_n$ with the next highest CE value (MaxCE, explained in the previous subsection). It then, attaches an expectation codelet to it, puts it into the WM to be executed by BN and waits for the user confirmation. If the cause of the error is $NODE_n$, CLM copies its action to the $NODE_f$'s cause and all information into the left part of the created rule R in CELTS' CM. Finally to save the traces of what was done to find the cause, 1) CLM creates a sequence of empty nodes similar to what is retrieved as the sequences of executed nodes from CELTS' LTM, 2) assigns $NODE_n$ to its first node and $NODE_f$ to the last node and 3) copies to the sequence created in CM all intermediate nodes between $NODE_n$ and $NODE_f$, and then creates links between them. The nodes $NODE_n$ and $NODE_f$ in this sequence are tagged as the cause and effect of the problem that caused the error.

However, if, in the execution of the node $NODE_n$ in the previous step, the resulting information brought back by the expectation codelet to WM does not meet the expected results, CLM then (Figure 6.2. STEP3) repeatedly searches for all the nodes of the sequence from $NODE_{n-1}$ to $NODE_1$ with the highest CE value but less than the $NODE_n$'s value and pursues the same previous processes as explained in steps one and two to find the cause of the error. This process will continue for the remaining nodes retrieved from CELTS' LTM if each attempt fails. If CELTS cannot find any cause, the message "I am not capable of finding the cause of the problem" is shown.

```
CausalMemoryConstructor( LTMPatterns, MaxCE,  NODE_f )

STEP1:     CREATE A NEW RULE R IN CAUSAL MEMORY

           R.RIGHT= NODE_f

           FIND the node NODE_P  in LMPatterns that was executed prior to
           NODE_f which has caused the error by looking in the BN.

           Attach an expectation codelet to Node_p. Then send Node_p to WM.

           IF ( GetUserConfirmationForCauseOfProblem() = True)

                    R.LEFT := NODE_P

                     NODE_f.Cause := NODE_P.Action

            END IF

STEP2   ELSE
```

```
            Search for the node NODE_n in LMPatterns such that CE = MaxCE

            Attach an expectation codelet to Node_n. Then send Node_n to WM.

              IF ( GetUserConfirmationForCauseOfProblem() = True)

                  R.LEFT := Node_n

                    NODE_f.Cause := Node_n . Action

                    saveTheTracesOfWhatHappened()

              END IF

STEP3     ELSE

              Initialize variables NodeTemp := null and MaxCE := 0.

            FOR EACH node NODE_k from NODE_n-1 to NODE_1 of LMpatterns

                IF(NODE_k.CE > MaxCE and NODE_k.CE < Node_n.CE )

                                      MaxCE := CE_n

                                    NodeTemp = Node_K.

                END IF

              END FOR

                Attach an expectation codelet to NodeTemp Then send
                NodeTemp to WM

                IF (GetUserConfirmationForCauseOfProblem() = True) and
                MaxCE > 0 )

                          NODE_f.Cause := NodeTemp .Action

                          R.LEFT:= NodeTemp
                  END IF
          ELSE
                      Show message "I have no solution" to user.
END
```

Figure 6.2 CELTS' Causal Memory construction algorithm

6.3.4 Using Mined Patterns to Improve CELTS' Behavior

The third part of CELTS' Causal Learning occurs in Step 7 and Step 8 of CELTS' cognitive cycle. It consists in improving CELTS' behaviour by making it reuse found rules to predict why users are making mistakes, determine how to best help them, and in some specific cases, to reconstruct the Causal Memory (CM). Finding causes will directly influence the actions that will be taken by CELTS' Behaviour Network (BN). CELTS' behaviour will improve due to the fact that the more it interacts with users and they confirm the correctness of the found causes for their mistakes or not, the more the estimated CE values for the nodes in the rules get reinforced or weakened. After some interactions between CELTS and the users (Figure 6.3 of CELTS' BN), Causal learning may find for instance a chain of interrelated nodes. The node V is usually in relation with node Y and node Y is in relation with node Z, according to users confirmations and minimum support and confidence defined by domain expert. For instance, CLM learned after several interactions with users that 60 % of the time "user chose the wrong joints → user makes the arm pass too close to the ISS". This means that after a while CELTS' CLM is capable of jumping from a start point in the BN to a goal and eliminates unnecessary nodes between them. However, jumping from one point to a goal point in the BN is not always a good decision as CELTS is a tutor and some intermediate nodes are very important hints to users. To solve this problem, in the first step, we tagged the important nodes in the BN as not to be eliminated. Thus, after some experiments to go from one point to the other (for instance in Figure 6.3.B nodes V → Z), CELTS' CLM makes an obligatory passage through intermediate nodes such as node Y and eliminates only unnecessary nodes between them. In the second step, to automatically eliminate unnecessary nodes that have not been pre-tagged by a human expert, we used the aforementioned algorithms (previous subsection Figure 6.3.STEP2 and STEP3) for finding causes when the users make an error while interacting with CELTS. This means that to achieve a goal from a start point in the BN, according to CELTS' experiences with users, CLM must decide to preserve important nodes and only eliminate those that are unnecessary (e.g., Figure 6.3.B two points v and z) in the BN. Reconstruction of CELTS' Causal Memory occurs when, following several interactions with users, CLM needs to alter it in order to establish the cause for a particular event. For instance, given a failure and its found cause in a rule R, for each interaction and according to the user's confirmation, CLM may augment or decrease the CE's values. Thus, if CLM finds that after several interactions with a user, a rule CE's value is higher than the regular rule CE's values, then CM might be altered for this event and reconstructed as explained in the STEP3' of the previous subsection.

Finally, it is worth noting that CELTS' BN is an acyclic graph. The Causal Markov Assumption (CMA) postulates that for any variable X, X is conditionally independent of all other variables in an acyclic causal graph (except for its own direct and indirect effects) based on its own direct causes. Accordingly, the refined BN produced by our Causal Learning algorithm could be considered a primitive proposition for the construction of a causal Bayesian network.

For instance, like the cars' side and front mirrors example given in the causal learning section of chapter II, after several interactions with users rules are extracted by the algorithms: 1) Forgetting camera adjustment (F) → Choosing Bad joint (B) → collision risk (C); 2) Choosing bad joint (B) ← Forgetting camera adjustment (F) → collision risk (C). If we assume that CMA holds, both structures in our example entail exactly the same conditional and unconditional independent relationships: In both, F, B and C are dependent and F and C are independent conditional on B (Gopnik et al., 2004).

6.4 EVALUATION AND RESULTS

To validate CELTS' Causal Learning Mechanism (CLM), we integrated it (Figure 6.4.C) into CELTS' consciousness viewer (Figure 3.8) and performed more than 250 CELTS executions of Canadarm2 in a simulator which included camera adjustments, collision risks and Canadarm2 bad manipulations as explained in chapters four and five. During each execution, CELTS randomly chose and executed one of the BN scenarios. After each CELTS execution, CLM extracted causal rules and used them for future interactions. The CLM learning process depends on three parameters: 1) the minimum causal support (explained in the previous section), 2) the minimum causal confidence (explained in the previous section) and 3) the learning rate, adjustable by the domain expert.

It must be noted that during the 250 CELTS executions, users answered differently for different situations and their response to CELTS' inquiries could either be always correct, always wrong, or random.

We predict that if CELTS is equipped with a Causal (CLM), Episodic (EPL) and Emotional Learning (EM) Mechanism, it should not only choose the best scenario having received the highest emotional valence, but also perform better and faster, finding the cause of the users' mistakes and eliminating unnecessary steps in the BN. The collaboration between these three mechanisms also helps CELTS to sometimes propose a better solution than what is initially offered by the domain expert.

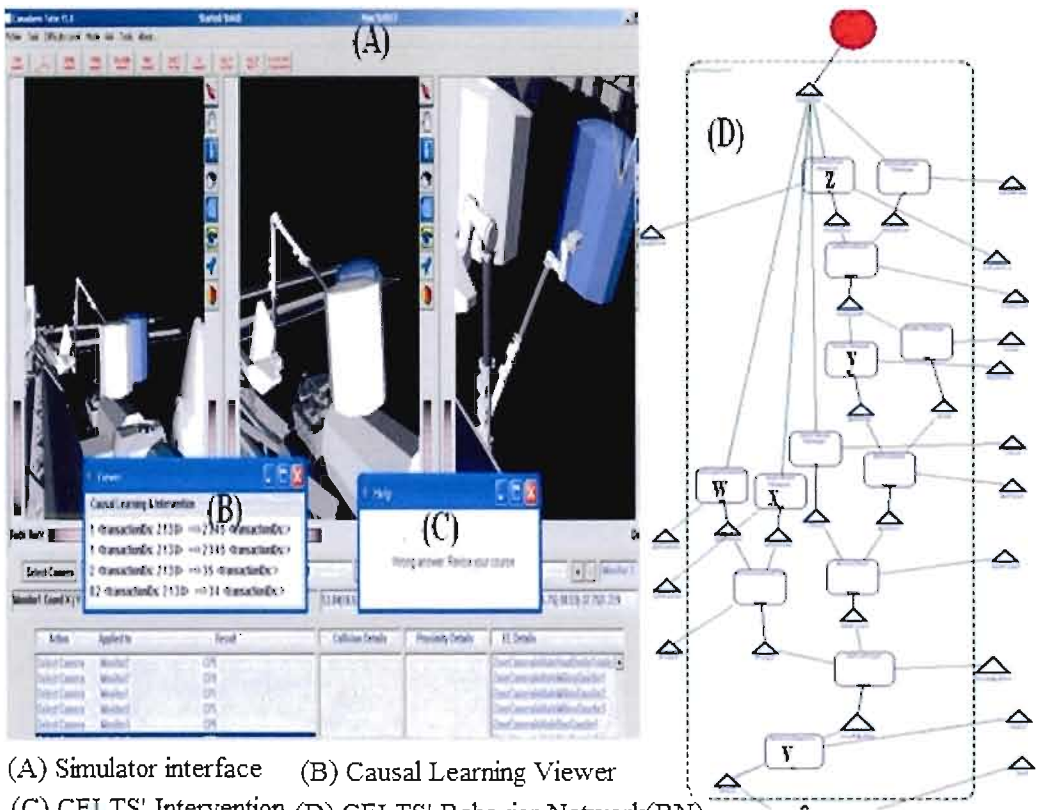
Experiment1: Approximate problem

It must be noted that when manipulating Canadarm2, it is important for the users to know the exact distance between the arm and ISS at all times. This prevents future collisions or collision risks with ISS. To help the user, an expert creates scenarios in CELTS' Behaviour Network (BN) (Figure 6.3.D). These scenarios are to help the user avoid collisions between the arm and ISS during manipulation of the arm. The four situations that CELTS can detect are the following in this type of experiment: 1) the user chose to move the wrong joint; 2) the user was tired; 3) the user did not remember his course or 4) the user has never passed through this zone on the ISS.

The scenario starts when CELTS detects that a user has chosen the wrong joint and is moving the arm too close to the ISS. CELTS first prompts the following message: *"Have you ever passed through this zone?"* If the answer given by the user is *yes*, CELTS asks the user to verify the name of the joint that he has selected. If the user fails to answer correctly, CELTS proposes a hint in the form of a demonstration or it stops arm manipulation. In this case, the user needs to revise the course before starting the arm manipulation again. If the user's answer is no, CELTS asks him to estimate the distance between the arm and ISS. If the user fails to answer correctly, CELTS will then ask the user if she/he is tired, has forgotten the lesson about this type of situation or if she/he needs some help. If the user answers correctly, it means that the user is an expert user and that the situation is not dangerous.

After several of these interactions with various users, CELTS found the following rules: 1) 60 % of the time, "the user chose the wrong joints → the user allows the arm to get too close to the ISS", (see for instance, Figure 6.3.D (V→W)); 2) 35% of the time, "the user has never passed through this zone → the user manipulates near ISS"; 3) 5% of the time, "the user is an expert → the user allows the arm to get too close to the ISS",.

It must be noted that the percentage value attributed to the extracted rules varies depending on the users' answers to CELTS' questions.



(A) Simulator interface (B) Causal Learning Viewer
(C) CELTS' Intervention (D) CELTS' Behavior Network(BN)

Figure 6.3 Causal Learning Mechanism intervention

Experiment2: Camera Adjustment Problem

As explained in chapters four and five, forgetting to adjust the camera prior to moving the arm increases collision risk (as depicted in Figure 6.3.A). From the interactions that occurred between CELTS and users to solve camera adjustment in chapter four, CLM drew the following conclusions: 1) 60 % of the time, "the user is tired → the user performs a camera adjustment error"; 2) 30 % of the time, "the user has forgotten this lesson→ the user performs a camera adjustment error" and 3) 10 % of the time, "the user lacks motivation → the user is inactive".

After some trials, CELTS' CLM is capable of inducing (by jumping from one point to another point in the BN, Figure 6.3.D) the source of the users' mistakes and proposing a solution for them in the virtual world. However, given that CELTS is a tutor and must interact with the user, jumping from the start point to the end of the scenario (Figure 6.3.D, V→Z) causes the elimination of some important steps in the BN. To prevent this, as mentioned before, we tagged the important nodes in the BN as *not to be eliminated*. Thus, after some experiments, to go from V→ Z, CLM obligatorily passed through intermediate nodes such as node *Y* (Figure 6.3.D). We call this process CELTS' partial procedural learning (**Step 8** of CELTS' cognitive cycle).

Experiment3: Complex situation

To evaluate the extent of CELTS' capabilities when equipped with CLM, EPL and EM, we decided to examine a very complex path in the virtual world. We considered an exercise between two ISS modules, JEMEF01 (labelled and is referred as A) and MPLM02 (labelled by red cube and is referred to as END) in the virtual world (as shown in Figure 6.4) in which users' mistakes while moving Canadarm2 from configuration A to END are very likely. (Figure 6.4.A).

As shown in Figure 6.4.A, Canadarm2 is very close to configuration A. Thus, the exercise starts near to the module A and finishes at module END. In the first step of this experiment, the user has handled the collision risk problem with the configuration A. In the second step, the user faces at least four paths, from configuration A to END (Figure 6.4.A). Importantly, the expert system has conceived only three scenarios in the BN regarding only three paths with their corresponding obstacles to be avoided: P1 (AECDH), P2 (AEBCDH), and P3 (AEFGHD) (Figure 6.4.B).

Whichever paths are chosen by the users, obstacles A, E, B, C, D, H, G, and F have to be avoided in the virtual world to prevent any collision. Therefore, the nodes in the BN corresponding to those obstacles in the virtual world are marked as "Not to be eliminated", by the domain expert.

The domain expert marks Configurations A, C and D as very important for the paths P1 and P2. Thus, in configuration C, in order to go through them without causing any collision risk, the user must first rotate camera8 60 degrees horizontally (Figure 6.4.A) and then choose the specific joint EP and then joint SP (Figure 3.6). In configuration D, the user must first adjust camera6 in order to have a good view of obstacles G and H before performing any movements. In path P3, the user must respect the following steps to prevent collision risk while manipulating Canarm2 from the configuration A to the END. First, in configuration E, camera2 must be turned 30 degrees, and the manipulation must then be continued using joint SR. Then, in configuration F, the joint SY must be selected and rotated 90 degrees to prevent any collision with ISS. In configuration G, the obstacle H must be avoided by rotating Canadarm2 60 degrees.

It must be noted that when we refer to the Episodic Scenario (see below in Part One) in this experiment, we mean that corresponding nodes in CELTS' BN (Figure 6.4.B) are marked as "*not to be eliminated,*" since our purpose here is to examine CELTS' capacity to find the best scenario among different solutions given by the expert. And when we refer to the Causal Scenario (see below Part two of this experiment), we mean that corresponding nodes in CELTS' BN (Figure 6.4.B) can be eliminated. Unlike EPL, CLM must find the cause of users' mistakes and eliminate unnecessary nodes between points L and T in the BN (Figure 6.4.B).

Thus, after a number of interactions with different users, we expect CELTS to propose the most emotionally positive paths from configuration K to L and eliminate unnecessary nodes between points L to T. The experiment is divided into two parts:

Part One (Episodic Scenario):

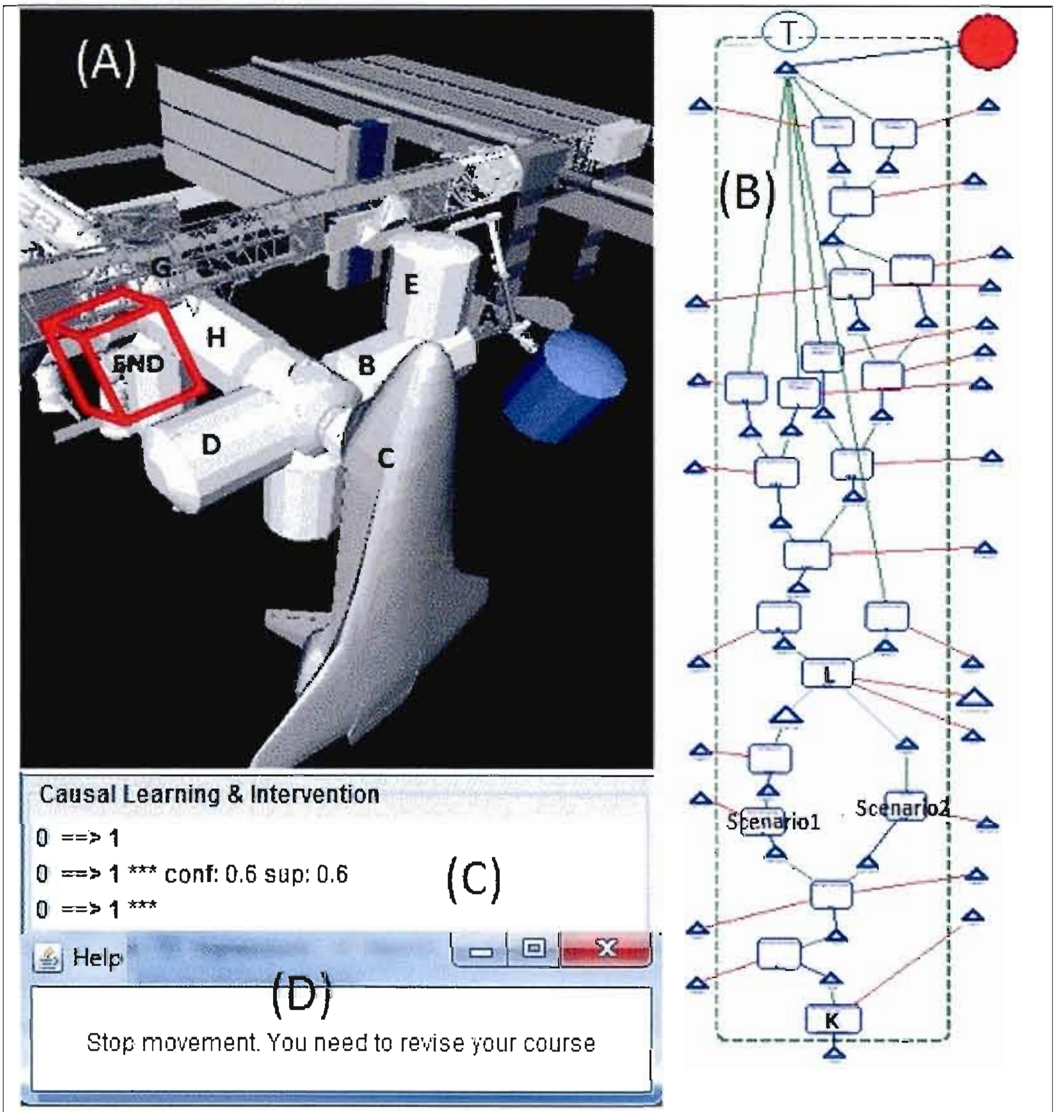
When the user (Figure 6.4.A) begins a manipulation and makes a mistake, the precondition of BN nodes activates and waits for the relevant information to fire corresponding nodes and demonstrate a message to the user. For instance, the BN node K activates when Canadarm2 approaches configuration A in the virtual world.

To help users handle the collision risk problem with configuration A, the domain expert conceived two paths in CELTS' BN (from points K to L in Figure 6.4.B) that correspond to this situation in the virtual world. After interacting with users, at point L, at the end of scenario1 and scenario2, CELTS asks an evaluation question to be sure that the hints or questions given to the users were useful and that users are aware of the collision risk in the virtual world.

It must be noted that due to the imminent collision risk, users' incorrect answers to CELTS' inquiries will activate the short route and trigger direct emotional interventions as explained in chapter four.

As during the collision risk experiment explained in chapters four and five, CELTS has here two choices to help users handle the situation. It can give a direct solution to the users (scenario2, Figure 6.4.B) or start by providing hints to help them handle the situation by themselves (scenario1, Figure 6.4.B).

After many executions, EPL extracted corresponding frequent event sequences for the first part of this experiment (Figure 6.4.BK-L), with a minimum support (*minsup*) higher than 0.45. Using the information extracted from this experiment, CELTS proposed scenario1 to help users prevent collision risk in the virtual world (Figure 6.4.B), because it contains a positive emotional valence as opposed to scenario 2.



(A) simulator interface (B) CELTS' Behaviour NetWork
(C) CELTS' Causal Learning Mechansim (D) CELTS' hints intervention

Figure 6.4 Causal Learning experiment

Part two (Causal Scenario):

In the second part of the experiment, after CELTS learned to choose the best scenario to help users prevent collision risk with configuration A (Figure 6.4.A) , users were asked to continue their manipulation and move Canadarm2 to the configuration END. CLM learned how to help users when they choose paths P1, P2, P3 to move Canadarm2 from configuration A to END based on the domain experts' hints and questions in the BN during the250 random executions mentioned at the onset of this section.

Here are the details. The extracted information from the second part of our experiment is 1) 50 % of the time, "the user is tired → the user forgot to adjust camera8"; 2) 40 % of the time, "the user is tired → the user performs a bad manipulation of Canadarm2"; 3) the remaineder10 % rules found by CLM are that "the user is tired → user must revise the course", "the user is tired → user did not make a collision risk", and "the user is tired → user wants to continue Canadarm2 manipulation". Note, however, that the third rule found by CLM is not always true.

Other extracted information demonstrated that 1) 50 % of the time, "the user forgot to adjust cameras → the user had a bad view of ISS' configurations and Canadarm2; 2) 20% of the time, the "the user had a bad view of ISS' configurations and Canadarm2 → the user caused a collision risk near obstacles C, D, E, and F"; 2) 20% of the time "the user forgot to adjust the cameras →the user manipulates very near to obstacles G and H"; 3) the remainder 10 % rules found by CLM are that "the user forgot to adjust cameras → the user must review the lesson", "the user forgot to adjust cameras → the user adjusted camera8", and "the user was not tired →the user forgot to answer questions".

Like the car' side and front mirrors example explained in the previous section *using mined patterns to improve CELTS' behaviour,* the extracted rules in this experiment demonstrate that if a user forgets to adjust the cameras in the virtual world, he/she will have a bad view of the virtual world and this will increase collision risk.

The extracted rules could be interpreted such that the probability of the user forgetting to adjust the cameras is independent of the probability of a collision with ISS' configurations, provided that the user has poor visibility in the virtual world. The extracted rules could also be interpreted such that the probability of having a poor view of ISS' configurations is independent of the probability of causing collisions in the virtual world provided that the user has forgotten to adjust the camera.

The percentage values CELTS attributed to the various possible causes are true most of the time, although they must be verified by a domain expert before use. These experiments demonstrated that CELTS is capable of choosing the best scenario for a given situation, selecting that which has received the highest positive emotional valence during its interactions with the users. It is furthermore capable of eliminating unnecessary nodes in the BN.

The text has referred up to now to paths 1 through 3 in the explanation of how to go from configuration A to END procedures. However, there exists a path P4 which could be considered as a shortcut.

The relevant obstacles to be avoided for this path are: A, E, and D. Ideally, CELTS would eventually ask users if they have some information about the obstacles they will encounter. However, CELTS cannot ask these questions when users choose path P4 prior to starting Canadarm2 manipulation, since the domain expert has not conceived relevant scenarios for this path (P4) in CELTS' BN. In this case, CELTS' CLM automatically connects to the *CanadarmTutor* database (Nkambou et al., 2006). The database contains different paths that users such as experts and novices have previously performed to move Canadarm2 on the ISS. Searching all the information about paths, CELTS' CLM, has the capacity of giving primitive hints to users when they encounter obstacles E, D and H in path P4.

One of our future goals would be to equip CELTS with the capacity of asking users about obstacles they might encounter in this path, before the manipulation starts.

6.4.1 CELTS' Performance after the Implementation of Causal Learning

We added a statistical tool to CELTS (Figure 6.5) that observes how association rule algorithm behaves when the number of recorded sequences increases. The experiment in the previous section was done on a 3.6 GHz Pentium 4 computer running Windows XP. Each CELTS interaction with user contains from four to 20 hints or questions depending on what the user answers and the choices CELTS makes. Each recorded sequence contained approximately 30 broadcasts. Figure 6.5 presents the results of the experiment. For all graphs, the X axis represents the executions from 1 to 250. The Y axis denotes execution times in graph A, and rule counts in graph B-D. The first graph (A) shows the time for mining rules which was generally short (less than 10 s) and after some executions remained low and stabilized at around 4 rules during the last executions. In our context, this performance was very satisfying. However, the performance of the rule mining algorithm could still be improved as we have not yet fully optimized all of its processes and data structures. In particular, in future works we will consider modifying the algorithm to perform incremental mining of rules. The second graph (B) shows the number of causal rules found after each CELTS execution. This would improve performance, as it would not be necessary to recalculate from scratch the set of patterns for each new added sequence. The third graph (C) shows the average number of behaviours executed (nodes in the BN) for each CELTS execution without CLM. It ranges from 4 to 8 behaviour broadcasts. The fourth graph (D) depicts, after the implementation of causal learning, the number of rules used by CELTS at each execution. Each executed rule means that CELTS skipped some unnecessary intermediate steps in the BN. The average number of executed rules for each interaction ranged from 0 to 4 rules. This means that CELTS generally used fewer nodes to perform the same task after the implementation of causal learning.

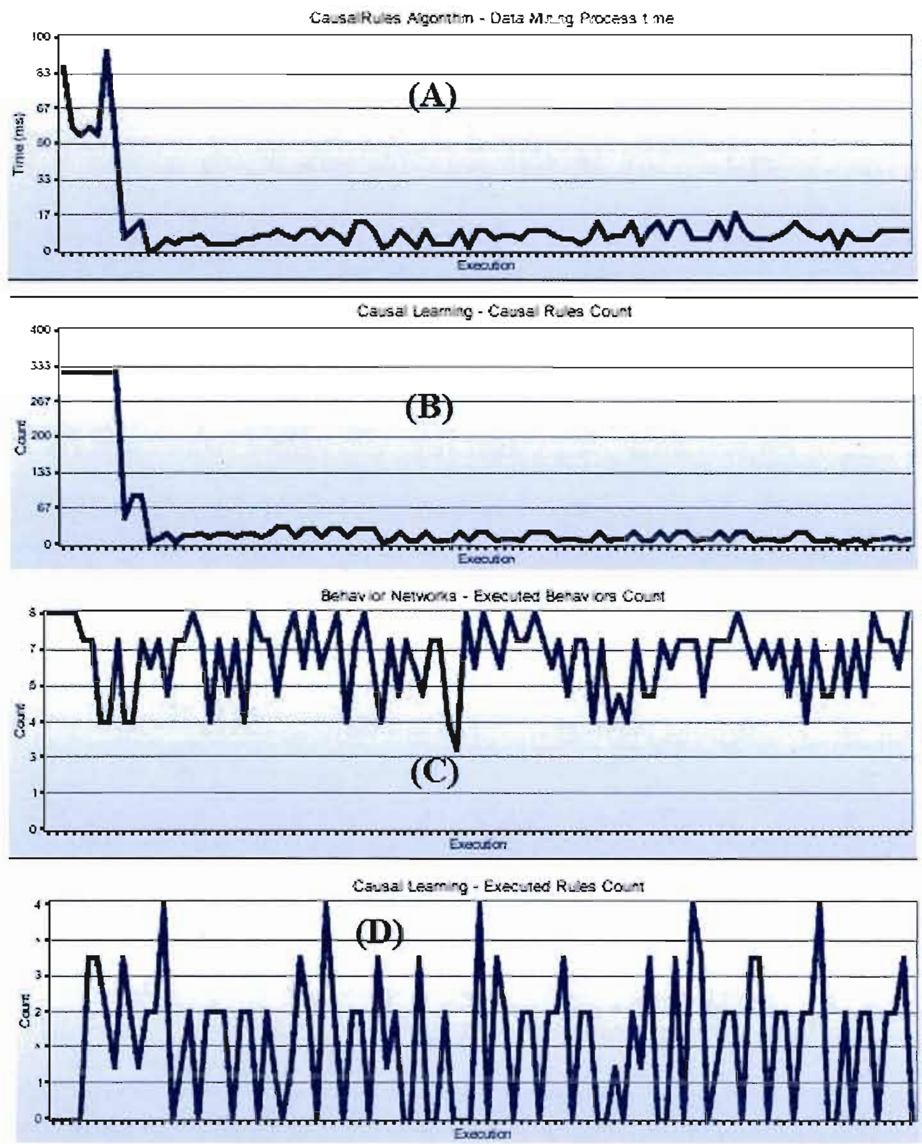


Figure 6.5 Causal Learning performance

6.5 CONCLUSION

In this chapter we proposed and implemented a Causal Learning Mechanism (CLM) for CELTS, in order to provide optimal tutoring assistance to users by inferring the likely causes of their mistakes in various situations. As in the case of humans, the episodic and causal memories in CELTS mutually influence each other during interactions with users. For instance, when the causes found by CELTS turn out to be false, this influences the support of the causal rules which in turn influences episodic memory- leading to a increase or decrease of the event supports.

To our knowledge, researchers in artificial intelligence have up to now limited themselves to designing causal reasoning and causal learning models for cognitive agents with Bayesian methods. However, the Bayesian approach is not suitable when agents such as CELTS face large amounts of data. This study, for the first time, creates a causal learning model for cognitive agents based on the sequential and temporal nature of the data stored in the system, combining sequential pattern mining algorithms and association rules. When equipped with CLM, CELTS is often capable of finding the causes of users' mistakes and proposing appropriate hints to help them.

CELTS is also capable of refining the BN by eliminating unnecessary nodes after several interactions with users. The refinement process could be considered as an alternative to the construction of a primitive version of a Bayesian Network structure. The suggested primitive network can then be verified and validated by a domain expert.

CHAPTER VII

CONCLUSION AND DISCUSSION

Human beings are endowed with emotions and different types of learning such as emotional learning, episodic learning, procedural learning, etc. (Rolls, 2000, Purves et al., 2008, Squire and Kandel, 1998). Emotions influence learning and decision-making (Damasio, 2000).The collaboration between emotions and different types of learning mechanisms helps guide the human decision-making process and the human capacity to better adapt to their dynamic environment. Thus, in order for a cognitive agent to resemble human agent, it must, at the very least, be equipped with different types of learning mechanisms and an emotional mechanism, and have those properly related to decision and adaptation.

Although many attempts have been made by researchers in artificial intelligence to implement emotions and different types of learning in cognitive agents, none have yet been completely successful. The setback is in part due to the fact that different types of learning are incompatible; the learning of explicit and implicit knowledge, for example.

However, after the implementation of emotions and various types of learning mechanisms in cognitive agents, one of the crucial tasks, is to find a way for these mechanisms to collaborate and help improve the decision-making process in the agent. In this study, we used energy levels, as explained by Maes (1989), for decision-making in CELTS' behaviour network, with however some modifications to allow the intervention of various types of learning. When faced with a problem, CELTS chooses and executes the most energetic solution, among the different solutions proposed by various modules. For instance, CELTS' Attention Mechanism may choose the most energetic coalition in the Working Memory, or CELTS' Emotional Mechanism may send enough energy to special nodes in the BN to fire them directly. In our model, emotional interventions influence all modules directly or indirectly.

In this study, we gave a preliminary solution to the implementation of different types of learning and emotions in CELTS. CELTS is equipped with both implicit and explicit learning. CELTS' learning mechanisms are implemented in a distributed and modular manner with emotions influencing all of them. They are Emotional learning, learning of Regularities, Procedural learning, Episodic learning and Causal learning. Implicit learning is unconscious and independent of the Attentional Mechanism (AM). It occurs in the Emotional Mechanism (EM), the Working Memory (WM) and the Behaviour Network (BN), whereas explicit learning occurs in different learning modules after information is broadcasted by the access consciousness (step 5 of cognitive cycle). All learning in CELTS occurs in a bottom-up fashion.

Through this study, we discussed in detail the integration of the following mechanisms:

a) An emotional mechanism and emotional learning

b) An episodic learning mechanism

c) A causal learning mechanism and partial procedural learning.

In the following, we summarize our contribution to these mechanisms and put forward their limitations as well as some interesting future work.

7.1 EMOTIONS

In chapter two, we pointed out that there is no consensus on the definition of emotions and how they emerge in humans. While psychological theories propose an abstract approach to the study of emotions, computational models propose a pragmatic framework for it. Thus, the implementation of emotions in a computational fashion impacts psychological theories by revealing their limits and hidden hypotheses (Marsella et al., In press). The implementation of emotions in computer science has taken two principal approaches. Some computer scientists are interested in using emotions to make their agents more believable, others work on the functional aspects of emotions and their influences on the agents' behaviour, learning and social aspects (Adam, 2007). In this study, we have adopted the latter approach.

Summary of our contributions

To implement an Emotional mechanism in their agent, most researchers in computer science have used a "Centralists" approach. In this study, we proposed a "peripheral-central" approach. The peripheral-central approach takes into account both the short and long route information processing and reactions, as in humans. Both the short and long routes perform in a parallel and complementary fashion in CELTS' architecture. The emotional mechanism and emotional learning mechanism described and implemented in this study intervene in both routes and interact with different parts of CELTS during consciousness broadcasting, during learning and during CELTS' reactions to the outside stimuli. This brings our artificial tutor closer to human-like behaviour. The emotional learning mechanism is kept aware of the ongoing situations and can, in real-time, learn and at the same time contribute emotional valences to the description of the situation. When it becomes "conscious", it may then contribute in a richer way to the decisions made and the learning achieved by the system. The new emotional learning mechanism thus offers greater flexibility in learning and behaviour adaptation. CELTS' emotional learning mechanism helps to drive its learning mechanisms to the most important elements in a situation to learn better.

Comparing to OCC model, our model propose: 1) a simplified implementation of emotions; 2) a detail discussion about the emergence of emotions in a cognitive agent. How emotional valences and intensities emerge and could be managed in a cognitive agent; 3) how the agent's assigns emotional states to behaviour.

As our experiment illustrates, when CELTS is equipped with this new emotional learning mechanism, it may, when needed, react more swiftly (i.e., react sooner in the cognitive cycle). The implementation of emotions in CELTS opens a door to cognitive scientists interested in the experimental aspects of emotions.

Limitations and Future works

One of the limits of the emotional mechanism proposed here is that the emotional valence assignment does not fit with the dimensional theory as explained by Russell and Lang (1980, 1993). The second issue to be explored in the future is the matter of how to make CELTS use its own emotions to make it more believable as an agent to the humans with which it has to interact.

7.2 EPISODIC MEMORY

Episodic memory is the memory of what, where and when. It allows people to mentally travel back through time as well as to imagine the future. Recently, studies have demonstrated the role of the hippocampus and its influences on episodic memory consolidation in the human brain. Two major memory consolidation theories are proposed by researchers: 1) the multiple-trace theory which postulates a hippocampus-dependent approach; and 2) the standard consolidation theory which postulates a hippocampus-independent approach.

The multiple-trace theory postulates that every time an event causes memory reactivation, a new trace for the activated memory is created in the hippocampus. Memory consolidation occurs through the reoccurring loops of episodic memory traces in the hippocampus and the construction of semantic memory traces in the cortex. Thus, the cortical neurons continue to rely on the hippocampus even after encoding. In this study, based on the current neuroscientific multiple-trace theory, we proposed the implementation of an Episodic memory and an Episodic Learning Mechanism in CELTS.

Summary of our contributions

To implement our proposed computational model of episodic learning, we used a data mining approach. As far as we know, no cognitive agent presently uses emotional valences and data mining algorithms to improve its behaviour. However, interaction between our agent and its dynamic environment generates large amounts of data. The data mining approach has proven very useful in extracting significant information from the large amount of data that it has to handle. During real time interactions with users, CELTS learns how to associate an event and its corresponding emotional valences with a partial/complete sequence of behaviours chosen by the Behaviour Network for execution. The emotional valence association to an event occurs according to the users' correct or incorrect answers to CELTS' questions. CELTS' EPL occurs in an unsupervised and bottom-up fashion.

In CELTS, the collaboration between the emotional mechanism and this episodic learning helps to choose the behaviour that is most likely to bring the agent to a self-satisfactory emotional state. The episodic learning is also useful when an expert system must propose different solutions to a problem. EPL can, after interactions with users, automatically decide which solution would best help users solve a given problem.

Limitations and Future works

However, the episodic learning algorithm used in this study is not incremental. For each CELTS executions, the algorithms must read the whole database. It would also be better that a computational model be built for the standard consolidation theory explained in chapter two and that it be compared with the multiple-trace theory.

We predict that the implementation of the computational model of the multiple-trace and the standard consolidation theories should impact psychological and neuropsychological theories by revealing their limits and hidden hypotheses.

7.3 CASUAL LEARNING

Causal learning is the process through which we come to infer and memorize an event's reasons or causes based on previous beliefs and current experience that either confirm or invalidate previous beliefs (Maldonado et al., 2007).

Summary of our contributions

The Causal Learning Mechanism (CLM) proposed in this study provides an optimal tutoring assistance to users by inferring the causes of the users' mistakes in various situations. To our knowledge, researchers in artificial intelligence have up to now limited themselves to Bayesian methods in order to design causal reasoning and causal learning models for cognitive agents. However, the Bayesian approach is not suitable when agents such as CELTS face large amounts of data. This study, for the first time, combines sequential pattern mining algorithms and association rules to devise a causal learning model for a cognitive agent based on the sequential and temporal nature of the data stored in the system. Causal knowledge is generated in CELTS after 1) the information is broadcasted in the system, 2) a decision is made about the ongoing problem, which 3) is reinforced by future experiences while CELTS interacts with its environment. The Emotional Learning mechanism operates through the activation it sends to the information in CELTS' WM. This causes specific pieces of information to be chosen by CELTS' Attention Mechanism. This information, if mined by the causal learning algorithm, will more likely be activated in the future when CELTS encounters similar problematic situations. CLM also helps partial procedural learning in CELTS' Behaviour Network (BN). After a certain number of similar experiences, CLM eliminates unnecessary nodes in CELTS' BN. Because of this, our mechanism could be considered as an alternative to a Bayesian algorithm. The important elements in CLM are the temporal occurrences of the events—the user's confirmations of causes found by CLM. A CLM-equipped CELTS has is capable of finding causes and propose appropriate hints to help users.

It is worth mentioning that episodic and causal memory in CELTS mutually influence each other during interactions with users. For instance, when the causes found by CELTS turn out to be false, this influences the support of the causal rules, which in turn influences episodic memory- leading to an increase or decrease of the event supports. Mutually, the reoccurrence of an event increases its support which in turn influences the cause of that event.

Limitations and Future works

However, the causal learning algorithms used in this study are not incremental. Therefore, for each CELTS executions, the algorithms must read the whole database. Another limit in our work is that given the observed data and the confidence and support calculated by CELTS' CLM, the question remains as to how one could produce the probability distribution as it exists in Bayesian Networks.

7.4 COMPARISON BETWEEN DIFFERENT ARCHITECTURES' LEARNING CAPABILITIES

Now we compare CELTS' learning capabilities with three popular architectures: LIDA, ACT-R and CLARION (Table 7.2).

First, we make a comparison between CTS and its emotional/learning version (CELTS) discussed in this study (Table 7.1). From chapter four to chapter six, we added new mechanisms to CTS. We first added the Emotional Mechanism and Emotional Learning. We then implemented the Episodic Learning Mechanism and observed its involvement with emotions. Finally, we added the Causal Learning Mechanism to obtain CELTS. In chapter six, we performed some experiments to verify CELTS' total capacity, given that it is equipped with EM, EPL, and CLM.

	CTS	CTS+EM	CTS+ EM + EPL	CTS+ EM + EPL + CLM = CELTS
Procedural Learning (Explicit/Implicit)	X	X	X	X
Emotional Learning	—	X	X	X
Episodic Learning	—	—	X	X
Emotional Learning help other types of learning	—	—	X	X
Causal Learning	—	—	—	X

Table 7.1 Comparison between CTS and CELTS (— =the architecture is not equipped with this specific learning; X = the learning mechanism is implemented)

The implementation of Episodic Memory (EM) and Learning (EPL) in LIDA and CELTS is very similar. In both, EPL consists of a declarative memory (DM) for the long-term storage of autobiographical and semantic knowledge and a short-term transient episodic memory (TEM). The Episodic Learning in both architectures occurs in bottom-up fashion. However, while LIDA uses variants of sparse distributed memory (SDM) to implement Episodic Memory, CELTS uses a sequential pattern mining approach. To implement our episodic learning, we chose the data mining approach because of its reliability when facing large amounts of data. Furthermore, using data mining algorithms in our agent made the simulation of the multiple-trace theory of memory possible. However, SDM has many setbacks when used for the implementation of episodic memory. First, given that SDM offers a very limited capacity of storage, adding new information makes previous information blurry in the memory information retrieval process. This is because new and previous information corrupt each other. According to Fan (1997), SDM performance for pattern recognition is good in theory, but not in practice.

CELTS' Episodic Learning occurs in an unsupervised fashion and a kind of reinforcement learning, for it depends on the user's answers to the questions or hints.

While the designers of LIDA, ACT-R and CLARION have only discussed the use and importance of Emotions and Emotional Learning in the different types of learning and decision-making in theoretical terms, in our study, we proposed an actual concrete architecture in which these elements have been implemented. .

While LIDA is not equipped with Causal Learning, CLARION is equipped with supervised learning. However, at this point, there is no computational model for causal learning proposed in CLARION. CELTS' Causal Learning Mechanism occurs in an unsupervised fashion and through a type of reinforcement learning, for it partially depends on the temporal occurrence of the events and the users' confirmation.

As is the case with LIDA's architecture, CELTS' bottom-up learning is implemented for all types of learning such as learning of Regularities, Emotional, Episodic, Procedural and Causal learning. CELTS is not equipped with Attention Learning. One of our interests is to find a way to integrate it into the architecture.

	LIDA (Franklin, 2006)	ACT-R (Anderson,2004)	CLARION (Sun, 2006)	CELTS (2010)
Explicit Perceptual Learning	X	—	X	—
Episodic Learning	X	X	—	X
Explicit Procedural Learning	X	X	X	X
Implicit Procedural Learning	—	X	X	X
Emotional Learning help other types of learning	—	—	—	X
Bottom-up Supervised Learning	X	—	X	X
Supervised Causal Learning	—	—	X	X
Unsupervised Causal Learning	—	X	—	X

Table 7.2 Comparison between LIDA, ACT-R, CLARION and CELTS (— =the architecture is not equipped with this specific learning; X = the learning mechanism is implemented)

To conclude this thesis, we present the cognitive and computer science contributions it makes to work on cognitive architecture.

7.5 CONTRIBUTION TO THE COGNITIVE DIMENSION

To propose our generic emotional architecture, emotional learning, episodic learning, and causal learning mechanisms, we drew from current neuroscientific models. The resulting architecture is more neurologically plausible, for it integrates a recent view of the amygdala's double role with respect to emotions. That is, emotions allow CELTS to learn, and then react swiftly in emotionally-burdened situations, as well as supply an emotional assessment to all sorts of stimuli in working memory which may be used for learning purposes. This might also accelerate learning speed for the emotionally-influenced information that enters working memory and is later broadcasted through CELTS' cognitive cycles. CELTS' processing is now also closer to human cognitive processing. In fact, from a cognitive-functional point of view, the agent is now better equipped to interact in a world where stimuli are not created equal, some being more pleasurable or more dangerous (physically or socially) than others. We believe that these generic learning mechanisms are also useful to generate testable hypotheses about aspects of human learning and open new lines of research in this domain. The algorithms are also adaptive and useful to other cognitive architectures such as LIDA, ACT-R and CLARION.

7.6 CONTRIBUTION TO THE COMPUTER SCIENCE DIMENSION

To implement emotions and various types of learning mechanisms in CELTS, we used several types of algorithms and methods, such as: a) in CELTS' Emotional mechanism the nodes' behaviour are simulated using a sigmoid function; b) to implement episodic learning we used sequential data mining algorithms; c) to implement causal learning we used a mix of sequential data mining and association rules algorithms. The algorithms used in this study were first developed and improved in GDAC before being integrated into CELTS. These algorithms contribute fundamentally to the improvement of cognitive agents' learning capabilities.

To our knowledge, no cognitive agent presently uses emotional valences or data mining algorithms to improve their behaviour. Now, CELTS can learn continually, adapt agilely to dynamic environments, and behave flexibly and intelligently when faced with new situations. Although CLM, EPL, and EM are implemented separately and in a modular fashion, they collaborate in parallel to help CELTS' decision-making mechanism. The integration of emotions in the machine and their collaboration with the other aforementioned learning algorithms is an important enhancement in cognitive agents learning capabilities. These algorithms could also be used in other cognitive or emergent agents to improve their performances.

According to Plato, human behaviour flows from three main sources: desire, emotion, and knowledge. Artificial agents have dealt well with desire and knowledge for some time now. Our proposal, we believe, takes us closer to the last great source of human behaviour: emotion.

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