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A biologically-inspired affective model based on cognitive situational appraisal

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A Biologically-Inspired Affective Model Based on Cognitive Situational Appraisal

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Abstract*—Although various emotion models have been proposed based on appraisal theories, most of them focus on designing specific appraisal rules and there is no unified framework for emotional appraisal. Moreover, few existing emotion models are biologically-inspired and are inadequate in imitating emotion process of human brain. This paper proposes a bio-inspired computational model called Cognitive Regulated Affective Architecture (CRAA), inspired by the cognitive regulated emotion theory and the network theory of emotion. This architecture is proposed by taking the following positions: (1) Cognition and emotion are not separated but interacted systems; (2) The appraisal of emotion depends on and should be regulated through cognitive system; and (3) Emotion is generated though numerous neural computations and networks of brain regions. This model contributes to an integrated system which combines emotional appraisal with the cognitive decision making in a multi-layered structure. Specifically, a self-organizing neural model called Emotional Appraisal Network (EAN) is proposed based on the Adaptive Resonance Theory (ART), to learn the associations from appraisal components involving expectation, reward, power, and match to emotion. An appraisal module is positioned within EAN contributing to translate cognitive information to emotion appraisal. The above model has been evaluated in a first person shooting game known as Unreal Tournament. Comparing with non-emotional NPC, emotional NPC obtains a higher evaluation in improving game playability and interest. Moreover, comparing with existing emotion models, our CRAA model obtains a higher accuracy in determining emotion expressions. .

***Index Terms*—self-organizing model, ART, neural network, affective model, agent.**

I. Introduction

Emotion is a complex phenomenon involving human being's psychological and physiological responses while interacting with the environment. It remains a challenge to explain the process of emotion generation as part of the "person-environment relationship". On the other hand, emotion modeling is important in understanding human behaviours. In addition, it also finds many applications, especially in designing virtual human characters in virtual worlds. Specifically, modeling of emotion could enrich virtual humans with lively facial expressions and behaviors, presenting motivated responses to their environment and intensifying their interactions with human users. Also, interactive agents with emotion modeling capability could form a better understanding of their user's moods and preferences and can adapt themselves to the user's needs [9]. As a result, the element of emotion makes virtual agents more human-like and appealing.

A key challenge in emotion modeling is to explain the mechanism of emotional process. In fact, this topic has been studied over a long period. Pioneering theories of emotion, such as the James-Lang Theory, the Cannon-Bard Theory, and the Two-Factor Theory focused on how emotion arises. Despite the differing views, it is generally agreed that emotion is the combinative outcome of numerous complicated external circumstances. In recent decades, "appraisal theories" has become the leading theory of emotion, which states that a person's emotion is his/her personal assessment of "person-environment relationship" based on events. Many computational emotion models have been proposed based on appraisal theories and psychological theories. Some focus on designing appraisal dimensions which need appraisal variables to be defined beforehand and evaluated in a subjective way [2] [13] [6]. Others focus on logical reasoning about the eliciting factors of emotions [8] [12] [24] [26]. They were proposed based on psychological models aimed at simulating real human emotion process. For example, EM [16], FLAME [8], FAtiMA [6], and ALMA [11] are proposed based on the OCC theory of emotion [18]. WASABI [2], and PEACTIDM [12] were inspired by Scherer's theory [22]. There are also some emotion models proposed based on Smith and Lazarus's appraisal theory [25]. However, most of these models need measurement for dimensions beforehand and rarely consider the role of cognitive regulation in emotion appraisal.

So far, numerous experiments by functional magnetic resonance imaging (fMRI), electroencephalography (EEG), electromyography (EMG), and skin conductance (SC) demonstrate that the mechanism of human emotion is highly associated with cognition and processed by multiple regions in human brain [19]. The objective behind this research is to propose a computational architecture which could realize the cognitive regulated affective process by integrating the cognition with emotion appraisals.

Two key factors are considered in this work. First, emotion model needs to mirror actual human emotions in the real world. Second, emotional appraisal should interact with personal cognition and experience, and based on environment feedback.

This paper proposes a bio-inspired computational model called Cognitive Regulated Affective Architecture (CRAA) based on the Adaptive Resonance Theory (ART) [5], the cognitive regulated emotion theory [17], and network theory of emotion [19]. This model contributes a compounded system which integrates the cognitive network, affective network and appraisals together to emulate the interactive functions among prefrontal cortex (PFC), anterior cingulate cortex (ACC) and amygdala in human brain. Moreover, a self-organizing neural model called Emotional Appraisal Network (EAN) is introduced to learn the associations from appraisal components involving expectation, reward, power, and match to emotions. The above model has been evaluated in a first person shooting game. Comparing with non-emotional NPC, the emotional NPC obtains a higher rating in improving game playability and interestingness. Moreover, comparing with other existing models, our CRAA obtains a higher accuracy in emotion generation.

The rest of this paper is organized as follows. Section II reviews the related work. Section III studies the neural substrates of emotion in brain. Section IV presents our Cognitive Regulated Affective Architecture (CRAA). Section V presents empirical experiments and comparison results. The final section concludes and discusses future work.

II. Related Work

This section reviews several emotion models proposed in the past years. Most of them focused on the designing of appraisal parameters and rules for emotion instances. Then emotion appraisal is realized via a set of IF THEN rules. Depending on different application objectives, various appraisal mechanisms and variables are individually designed without a unified framework.

El-Nasr *et al.* present FLAME based on the OCC model [18] and the "event-appraisal model" [21] [8]. FLAME maps the assessments of events with goals into emotions using a fuzzy method. Action selection is then associated with specific emotions by fuzzy rules in a simple but friendly relationship. FLAME is designed for virtual pets instead of for simulating human emotions.

Marinier *et al.* [12] describe PEACTIDM, a computational structure to support emotional appraisal based on Scherer's theory [22]. Emotion is decided by six dimensions: suddenness, goal relevance, intrinsic pleasantness, conduciveness, control and power. The variables and rules need to be defined and evaluated subjectively.

Marsella and Gratch [13] build EMA based on the dynamic of emotional appraisal. The appraisal frame of EMA is designed with a set of variables which are used to evaluate the "significant events" defined to refer the events that can facilitate or inhibit a state. Emotions are categorized mainly by the variables of relevance, desirability, likelihood, causal attribution, and coping potential. EMA is a well designed model instead of a learning model. Therefore it's still limited in emulating the personalized human emotions.

Becker-Asano *et al.* [2] develop WASABI, which simulates appraisal processes based on the pleasure-arousal-dominance (PAD) space and Scherer's sequential-checking theory [22]. The three-dimensional emotion space describes all events in terms of three dimensions named pleasure, arousal and dominance. This architecture is easy to be applied in various virtual spaces, but difficult to be integrated with cognitive architecture and handle complex cognitive situations.

FAtiMA is proposed by Dias *et al.* [6] as a two-layered architecture to create virtual agents based on OCC theory [18]. In FAtiMA, the appraisal of emotion is mainly around the objective evaluation of three elements: the desirability of the event, the desirability of the object and the like relation between agent and the object. This method is however too simple to deal with complex situations.

There are also a few models focusing on designing dynamical models to simulate the emotional part of brain, such as the flow model [15], the amygdala simulated model [14], and the BELBIC model [23]. However, these models either do not associate cognition with emotion or do not model expressible emotion instances.

III. Neural Substrates of Emotion

A. Relation between cognition and emotion

While cognition refers to the processes involving memory, attention, and decision, emotion arises from the evaluation of events through an appraisal process. In human brains, cognitive and emotions are tightly interacted instead of separated systems. For example, the prefrontal cortex (PFC) and anterior cingulate cortex (ACC) not only have a central role in cognitive control but also involve in assessing emotions. The core of affective regions, amygdala also has been confirmed to response depending on attention, and closely link to perception [19]. In fact, the theory of cognitive regulated emotion has been supported by functional magnetic resonance imaging (fMRI) examination [17]. It shows that the cognitive regulation process includes three steps: strategy generating for cognitively coping emotional events associated with working memory processes localized in the lateral PFC; interference between reappraisals and evaluations to generate an affective response associated with the dorsal anterior cingulate cortex; and reevaluating between internal states and external stimuli associated with medial PFC. And the emotional process is to evaluate the stimulus as affectively significant associated with two highly interconnected brain structures: the amygdala and medial orbital frontal cortex [17].

B. Network theory of emotion

The network theory of emotion argues that emotion affects behavior through a network form in human brains. This argument has been supported by studies of neural systems, via fMRI based experiments [19]. Specifically, the network theory demonstrates that emotions are aroused by a network of multiple brain areas, each in charge of different functions. Figure 1 shows that brain areas (for example, A2) are connected to form networks (for example, Network1) and involved in multiple neural computation modules (for example, NC2, NC3, and NC4). Pessoa's conceptual proposal demonstrates a network structural topology for neural computations of emotion. Specifically, emotion is one of the functions generated by human brains through a plenty of neural computation of modules (eg: perception, memory, learning, decision and execution) [19] and interacts with personal cognition. This proposal also demonstrates several principles for emotion modeling: First of all, emotion is generated not by an isolated region, but through the network of multiple areas in human brain. Secondly, emotion architecture is a complex network which comprises multiple modules and neural computations. Finally, emotion needs to be integrated with other inner states in order to take further impact on behavior. This view has inspired us to explore an emotion model which integrates multiple brain functions and processes such as perception, mental state, learning, and decision making within a network topology, in order to simulate the emotion function in human brains.

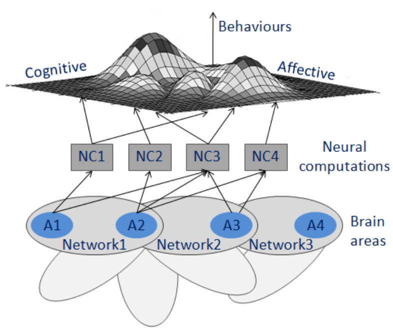

Fig. 1. Pessoa's conceptual proposal of neural computations and emotion. (Adopted from [19])

IV. Cognitive and Affective Architecture

This paper proposes a Cognitive Regulated Affective Architecture (CRAA), which comprises a cognitive network, an affective network and an appraisal layer based on Adaptive Resonance Theory (ART) [5], theory of cognitive regulated emotion [17] [19], and Pessoa's network theory of emotion [19]. Figure 2 shows the integrated cognitive-affective architecture which simulates the functions and interactions of prefrontal cortex (PFC) by cognitive network, anterior cingulate cortex (ACC) by appraisal layer, and the amygdala by affective network. The affective network and appraisal layer together compose the Emotional Appraisal Network (EAN), wherein cognitive network is highly interconnected with affective network through the appraisal layer in real time.

Firstly, the cognitive network receives sensory information and takes charge of decision makings based on the content in the working memory. Imitating the role of ACC, the appraisal module then generates affective information by evaluating the cognitive information involving the context situation, the perception, and the inner states. And finally, the affective network associates these appraisals to determine an emotion instance. The following sections describe the design of computational modules in details.

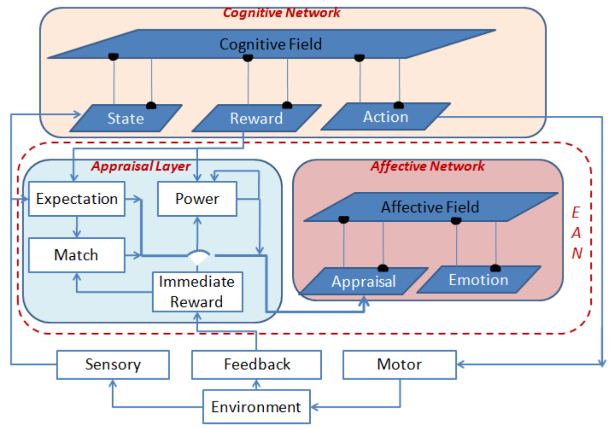

Fig. 2. Cognitive Regulated Affective Architecture (CRAA)

A. Cognitive Network

Emotional appraisal is not independent but highly depends on cognitive information. The cognitive network is designed to emulate executive functions in prefrontal cortex (PFC) such as strategy generating for coping emotional events, associating with working memory, and integrating the affective and motivational information.

Shown in Figure 2, the cognitive network employs a multi-channel architecture, comprising a cognitive field and three input fields, namely a sensory field for representing current states, an action field for representing actions, and a reward field for representing reinforcement values.

Cognitive network is designed as a Q-learning based cognitive architecture, called Temporal Difference Fusion Architecture for Learning, COgnition, and Navigation (TD-FALCON) [28]. TD-FALCON is a self-organizing neural network that incorporates Temporal Difference (TD) methods to estimate and learn value functions of action-state pairs $Q(s, a)$ that indicates the goodness for a learning system to take a certain action a in a given state s. Given the current state s, the cognitive network first choose an action a to perform by following an action selection policy. After perform the action, a reward may be received from the environment. Then the cognitive network observe the next state s', and pre-select an action a' with the maximal $Q(s', a')$ value. Upon receiving a feedback from the environment, a TD formula is used to compute a new estimate of the Q value of performing the chosen action a in the current state. The new Q value is then used as the teaching signal for TD-FALCON to learn the association of the current state and the chosen action a to the estimated Q value. A summary of the action selection policy and the direct code access procedure, based on fuzzy ART operations [3] is described in [27].

B. Appraisal Layer

A network-form appraisal frame, Emotional Appraisal Network (EAN) is proposed based on the network theory of emotion. This compounded network comprises of two main modules: one is an appraisal layer which is designed to simulate the such functions in anterior cingulate cortex (ACC) as anticipation of tasks and attention; another is the affective network designed to simulate emotion decisions in amygdala.

Four ACC neurons are encoded in the appraisal layer to evaluate the desirability of the actions, including the evaluation of expectation, immediately perceived reward, power of confidence, and perceived match, which are appraised dynamically based on the cognitive information of context, inner state, and perceptions. These neurons are identified as an assembly of four appraisal components by associating emotion with multiple modules and pathways based on the Pessoa's conceptual proposal of emotion (Figure 1). The appraisal layer provides a unidirectional translation of information from cognitive space to emotional space. The four appraisal factors are defined as follows:

Expectation: Expectation E represents what is considered the most likely to happen when a person takes an action in a situated environment. Expectation is considered as a key point for emotional appraisal. It has been generally taught that the emotion intensity increases as the expectation of positive result or negative avoidance increases [20]. In our model, expectation is adopted to demonstrate the agent's personal evaluation of a possible outcome which occurs subsequently after taking a specific action. Therefore, expectation should be associated with situations, actions, and must depend on the agent personal experience. Expectation is measured dynamically based on the evaluation of context including the agent's experienced and present performance. Here we define expectation formally as

$$E = Q(s, a), \tag{1}$$

where $Q(s, a)$ calculates the expected reward for taking action a under the state s based on Q-learning algorithm. Thus, expectation demonstrates a pre-evaluation of the benefit of the action to be taken.

Reward: Reward R refers to the feedback stimuli sensed from environment and can be presented in the process of behavior. Reward is believed to be an indispensable component in the process of cognitive learning and emotions [25]. Recent research proves that amygdala, the core region for emotion in human brain, could mediates an arousing effect of reward and also links the sensory properties of reward to emotion [1]. Here the reward signal is sensed from real-time immediate feedbacks I_f given by environment, with a value in the range of [0,1]:

$$R = I_f. \tag{2}$$

Usually, reward occurs subsequently after taking an action.

Power: Power P refers to the inner state of one's confidence. It's described as the state of having confidence in oneself for achieving the goal. That means, power is built by accumulation of one's own experience and affected by perceived feedbacks and the previous power level. Therefore, in real time, power is updated by a temporal difference equation (3) depending on the feedback information and the current self-confidence level:

$$P(t + 1) = P(t) + \alpha(1 - P(t))\gamma, \tag{3}$$

where $P(t + 1)$ and $P(t)$ represent the values of power in time $t + 1$ and t respectively, and parameters $\alpha \in [0, 1]$ and $\gamma \in [0, 1]$ are the *decay index* and *gain index* respectively.

Match: Match M is adopted to measure the difference between expectation and the real feedback information. It demonstrates how much the result could satisfy the expectation. Here, match is calculated based on the context performance and perceived feedbacks, to evaluate how much the action could satisfy the expectation and updated by

$$M = 1 - |E - R|. \tag{4}$$

In real time, the above appraisal components are calculated dynamically based on the cognitive process which associates with the Q-learning and behavior selection policy. After receiving these information, affective network then processes emotional appraisal to predict the most appropriate emotion instance.

C. Affective Network

Affective network is designed to simulate the functions in amygdala, such as remembering emotional events and processing emotional reactions. As shown in Figure 2, the affective network employs a multi-channel architecture, comprising an affective field and two input pattern fields, namely an appraisal field for representing appraisal components and the emotion field for representing emotion instances.

As a sub-network in Emotional Appraisal Network (EAN), the affective network is proposed to learn the emotion association function of

$$E_m = f(E, R, P, M), \tag{5}$$

where E, R, P and M correspond to the sensed information from the appraisal layer: namely expectation, reward, power and match respectively. E_m denotes the set of emotion instances. The EAN then realizes cognitive regulated emotion by information transition through the appraisal layer.

The affective network is also built based on a generalization of the Adaptive Resonance Theory (ART) models [5], called fusion ART [28], for learning cognitive nodes across multi-channel mappings simultaneously across multi-modal input patterns. The affective network comprises an affective field F_2 and two input pattern fields (F_1^{ck}, $k = 1, 2$) through bidirectional conditionable pathways (Figure 3). The appraisal layer is connected to the input channel therefore transiting information into affective network to realize regulation. The dynamics of affective network, based on fuzzy ART operations [3], is summarized as follows.

Input vectors: Let $\mathbf{I}^{ck} = (I_1^{ck}, I_2^{ck}, \ldots, I_n^{ck})$ denote the input vector, where $I_i^{ck} \in [0, 1]$ indicates the input i to channel ck. With complement coding, the input vector $\mathbf{I}^{ck}$ is augmented with a complement vector $\bar{\mathbf{I}}^{ck}$ such that $\bar{I}_i^{ck} = 1 - I_i^{ck}$.

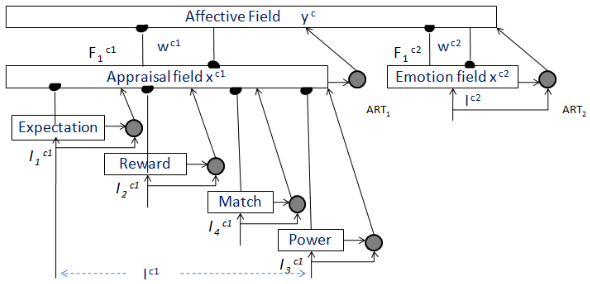

Fig. 3. The neural model of affective network.

Activity vectors: Let $\mathbf{x}^{ck}$ denote the F_1^{ck} activity vector for $k = 1, \ldots, K$. Let $\mathbf{y}$ denote the F_2 activity vector.
Weight vectors: Let $\mathbf{w}_j^{ck}$ denote the weight vector associated with the jth node in F_2 for learning the input patterns in F_1^{ck} for $k = 1, \ldots, K$. Initially, F_2 contains only one *uncommitted* node and its weight vectors contain all 1's.
Parameters: The fusion ART's dynamics is determined by choice parameters $\alpha^{ck} > 0$, learning rate parameters $\beta^{ck} \in [0, 1]$, contribution parameters $\gamma^{ck} \in [0, 1]$ and vigilance parameters $\rho^{ck} \in [0, 1]$ for $k = 1, \ldots, K$.

1) Appraisals Updating: Based on fusion ART, the affective network responses to incoming information in a continuous manner. The processing cycle comprises five key stages, namely code activation, code competition, activity readout, template matching, and template learning, as described below. At the beginning of each processing cycle, the four neurons encoding incoming information in the appraisals layer need to be updated. The appraisal information will be sensed in the affective network in order to realize cognitive regulated emotions. I_1^{c1} to I_4^{c1} denote the input neuron values for channel F_1^{c1} and are updated according to the following rules.

Four input signals are regulated synchronously by sensing from the neurons in the appraisal layer. I_1^{c1} is regulated by the expected reward of the action and updated by $I_1^{c1} = E$. This demonstrates the pre-evaluation of the payoff by taking a specific action. I_2^{c1} is regulated by the real-time feedback from the environment and updated by $I_2^{c1} = R$. I_3^{c1} is regulated by the inner state of power, and updated by $I_3^{c1} = P$. Finally, I_4^{c1} is regulated by the evaluation of how much the action could meet the expectation and updated by $I_4^{c1} = M$. Once the appraisal information transits from the appraisal layer to the affective network, emotion learning can proceed.

2) Emotion Learning: The fusion ART learns an emotion policy which maps directly from input patterns to desired emotion instances. Given the expectation E, immediate reward R, power P, match M, and the emotion instance E_m, the input vectors are set as $\mathbf{I}^{c1} = C(E, R, P, M)$ and $\mathbf{I}^{c2} = C(E_m)$, where C denotes the complement coded function for the input patterns.

This model then performs code activation to select a category node J in the F_2^c field to learn the association between E, R, P, M and E_m. The detailed algorithm is presented as follows.
Code activation: Given the input vectors $\mathbf{I}^{c1}, \ldots, \mathbf{I}^{cK}$, for each F_2 node j, the choice function T_j is computed as follows:

$$T_j = \sum_{k=1}^{K} \gamma^{ck} \frac{|\mathbf{I}^{ck} \wedge \mathbf{w}_j^{ck}|}{\alpha^{ck} + |\mathbf{w}_j^{ck}|}, \tag{6}$$

where the fuzzy AND operation $\wedge$ is defined by $(\mathbf{p} \wedge \mathbf{q})_i \equiv min(p_i, q_i)$, and the norm $|.|$ is defined by $|\mathbf{p}| \equiv \sum_i p_i$ for vectors $\mathbf{p}$ and $\mathbf{q}$.
Code competition: A code competition process follows under which the F_2 node with the highest choice function value is identified. The winner is indexed at J where

$$T_J = \max\{T_j : \text{for all } F_2 \text{ node } j\}. \tag{7}$$

When a category choice is made at node J, $y_J = 1$; and $y_j = 0$ for all $j \neq J$. This indicates a winner-take-all strategy.
Activity readout: The chosen F_2 node J performs a readout of its weight vectors to the input fields F_1^{ck} such that

$$\mathbf{x}^{ck} = \mathbf{I}^{ck} \wedge \mathbf{w}_J^{ck}. \tag{8}$$

Template matching: Before the activity readout is stabilized and node J can be used for learning, a template matching process checks that the weight templates of node J are sufficiently close to their respective input patterns. Specifically, resonance occurs if for each channel k, the *match function* m_J^{ck} of the chosen node J meets its vigilance criterion:

$$m_J^{ck} = \frac{|\mathbf{I}^{ck} \wedge \mathbf{w}_J^{ck}|}{|\mathbf{I}^{ck}|} \geq \rho^{ck}. \tag{9}$$

If any of the vigilance constraints is violated, mismatch reset occurs in which the value of the choice function T_J is set to 0 for the duration of the input presentation. Using a *match tracking* process, at the beginning of each input presentation, the vigilance parameter ρ^{ck} in each channel ck equals a baseline vigilance $\bar{\rho}^{ck}$. When a mismatch reset occurs, the ρ^{ck} of all pattern channels are increased simultaneously until one of them is slightly larger than its corresponding match function m_J^{ck}, causing a reset. The search process then selects another F_2 node J under the revised vigilance criterion until a resonance is achieved.
Template learning: Once a resonance occurs, for each channel ck, the weight vector $\mathbf{w}_J^{ck}$ is modified by the following learning rule:

$$\mathbf{w}_J^{ck(\text{new})} = (1 - \beta^{ck})\mathbf{w}_J^{ck(\text{old})} + \beta^{ck}(\mathbf{I}^{ck} \wedge \mathbf{w}_J^{ck(\text{old})}). \tag{10}$$

Code creation: Our implementation of Fusion ART maintains ONE uncommitted node in the F_2^c field at any one time. When an uncommitted node is selecting for learning, it becomes *committed* and a new uncommitted node is added to the F_2^c field. Fusion ART thus expands its network architecture dynamically in response to the input patterns.

3) Emotional Appraisal: Given the input vectors, the fusion ART model selects a category node J in the F_2^c field which determines the current emotion. For emotion decision, using complement coding, the input vectors $\mathbf{I^{c1}}$ and $\mathbf{I^{c2}}$ are initialized as $\mathbf{I}^{c1} = (I_1^{c1}, I_2^{c1}, I_3^{c1}, I_4^{c1}, \bar{I}_1^{c1}, \bar{I}_2^{c1}, \bar{I}_3^{c1}, \bar{I}_r^{c1})$ and $\mathbf{I}^{c2} = (1, ..., 1)$. The model then searches for the affective

TABLE I
THE EVENT SET

No.	*Event*	*No.*	*Event*
1	collected a weapon	5	damages enemy
2	collected a health package	6	kills an enemy
3	collected ammos/armor	7	killed by enemy
4	damaged by enemy		

node which matches with the current input using the same code activation and code competition processes according to equations (6) and (7).

Upon selecting a winning F_2^c node J, the chosen node J performs a readout of its weight vector into the affective field F_1^{c2} such that

$$\mathbf{x}^{c2} = \mathbf{I}^{c2} \wedge \mathbf{w}_J^{c2}. \tag{11}$$

The model then examines the output activities of the emotion vector $\mathbf{x}^{c2}$ and selects an emotion e_I, which has the highest activation value

$$x_I^{c2} = \max\{x_i^{c2} : \text{for all} \quad F_1^{c2} \quad \text{node} \quad i\}. \tag{12}$$

V. EXPERIMENTS

A. Virtual World Embodiment

Unreal Tournament (UT) [29] is a first person shooting game, which does not merely offer an environment for gaming, but also provides a platform for building and evaluating autonomous agents. We have built an emotional Non-Player Character (NPC) in UT game, by integrating our Cognitive Regulated Affective Architecture (CRAA) with behavior policies. The NPC is embedded with perception and sensor modules, and could capture what has happened in their surrounding areas. In the "Deathmatch" game scenario, every NPC must fight with any other player in order to survive and win. Our emotional NPC is supposed to show appropriate emotions when it encounters various events. Table I shows the emotional events that happen in the environment. These events provide the context of scenario, and are usually resulted from one or a sequence of actions. The emotion set is designed by adopting Ekman's six basic emotions: anger, disgust, fear, happiness, sadness, and surprise [7].

B. Experiment Methodology

Adaptive Resonance Theory (ART) based emotion learning model has been verified in abilities of emulating human emotions with comparable accuracy and adapting limited emotion rules to extended situations [10]. In this work, the emotion rules shown in Table II are learnt from human patterns by setting the parameters in EAN as follows: choice parameter $\alpha^{ck} = 0.1$ for $k = 1, 2$; learning rate parameter $\beta^{ck} = 0.1$ for $k = 1, 2$; contribution parameter $\gamma^{ck} = 1$ for $k = 1$ and $\gamma^{ck} = 0$ for $k = 2$; and vigilance parameter $\rho^{ck} = 1$ for $k = 1, 2$. All the input attributes have been normalized by complement coding [4]. Therefore the rules obtained from learning represent each attribute value in a range of $[x, \bar{x}]$. As

TABLE II
SAMPLE EMOTION RULES

No.	E	R	P	M	*Emotion Instances*
1	(0,1)	(0,1)	(0,1)	(1,0)	Sad
2	(1,0)	(0,1)	(0,1)	(0,1)	Sad & Surprise
3	(0,1)	(1,0)	(0,1)	(0,1)	Happy & Surprise
4	(1,0)	(1,0)	(0,1)	(1,0)	Happy
5	(0,1)	(0,1)	(1,0)	(1,0)	Disgust
6	(1,0)	(0,1)	(1,0)	(0,1)	Anger & Surprise
7	(0,1)	(1,0)	(1,0)	(0,1)	Happy & Surprise
8	(1,0)	(1,0)	(1,0)	(1,0)	Happy
9	(0,1)	(1,1)	(0,0)	(1,1)	Fear

TABLE III
THE EMOTION SET (ADOPTED FROM [7]) AND WORD EXPRESSION

No.	*Emotion*	*Emotion expression*
1	Anger	Dammit!
2	Disgust	Disgusting!
3	Fear	Gosh!
4	Happiness	Haha!
5	Sadness	Oh! No!
6	Surprise	Oops!

shown in Table II, (1,0) means TRUE, (0,1) means FALSE and (0,0) means Don't Care. Parallel triggering is designed by referring to the theory of compound emotion [18], which states that emotion rules could trigger more than one emotion instances at once. Thereafter, we create an emotional NPC by embedding the EAN in. In real time performance, EAN retrieves emotion knowledge by setting the parameters as follows: choice parameter $\alpha^{ck} = 0.1$ for $k = 1, 2$; learning rate parameter $\beta^{ck} = 1$ for $k = 1, 2$; contribution parameter $\gamma^{ck} = 1$ for $k = 1$ and $\gamma^{ck} = 0$ for $k = 2$; and vigilance parameter $\rho^{ck} = 0$ for $k = 1, 2$.

C. Emotion Expression

As it is difficult for NPC's to show facial expressions in a first-person shooting game due to their fast pace motions, we design specific interesting words for NPCs to express their affective status (shown in Table III). One or more emotion instances will be triggered when one of the events in Table I happens. As long as one of the emotion instances is triggered, the NPC will broadcast the corresponding text message to the chat box which is shown on UT interface to facilitate the players to communicate with each other. Thus, each player involved in the game can see the message in real-time. Figure 4 (a) and (b) show the snapshots of games with emotional NPC and non-emotional NPC respectively. We see the emotional NPC could express its affective status dynamically by uttering emotional expressions. Table IV shows some sample words uttered by the emotional NPC when emotional events happen.

D. Human User Evaluations

Firstly, we compare our CRAA model with several recently proposed models, namely EMA [13], FAtiMA [6] and WASABI [2], as they provide clear and specific emotion appraisal rules. We adopt these models into our application and evaluate their accuracy using real human evaluation. By taking

TABLE IV
SAMPLES OF THE EMOTION EXPRESSIONS

No.	Event	Emotion	Emotion expression
1	Collect a weapon	Happy	Haha! I got a new weapon.
2	Damaged by enemy	Angry &Surprise	Dammit! Oops! I was shot.
3	Collect a health package	Happy & Surprise	Haha! Oops! I got a health package
4	Killed by enemy	Disgust	So disgusting! I was killed.
5	Damages enemy	Happy & Surprise	Haha! Oops! I damage the enemy.

Fig. 4. (a) The emotional NPC. (b) The non-emotional NPC.

a questionnaire-based approach, we replace their application scenarios with ours and ask the subjects to evaluate the appraisal variables in these models. To make those appraisal dimensions easy to be understood, we further formulate them into questions and also cite their explanatory note from their original papers. Before the experiments, we give the subjects a short training so that they understand these models correctly. The questionnaire lists the same situations as in our experiment, leaving out the evaluation of appraisal variables. Then we distribute another questionnaire which lists the same situations as in the previous one, but subjects are asked to state their own appraised emotions. Thereafter, we collect the questionnaires and calculate the accuracy. Ten subjects aged between 20 and 30 are randomly selected from the computer school with a gender ratio of 7:3, considering male users are typically more experienced in first person shooting games than females. The results are calculated by averaging across ten subjects.

Table V shows the performance of EMA, FAtiMA, WASABI and our model in terms of their emotion prediction. Apart from CRAA, most models achieve less than satisfactory accuracy: 60% for EMA, 55.7% for FAtiMA, and 54.3% for WASABI. The low level of accuracy may be due to two reasons. Firstly, their models are static and limited by predefining the emotion rules subjectively. The predefined

TABLE V
ACCURACY OF CRAA AND OTHER MODELS

No.	Model	Accuracy
1	EMA	60.0%
2	FAtiMA	55.7%
3	WASABI	54.3%
4	CRAA	87.0 %

TABLE VI
EVALUATING THE ACCURACY OF EMOTION EXPRESSION

No.	Questions
1	I think the emotional NPC's verbal message could express emotions.
2	I think the emotion expressions are appropriate.
3	I think the emotional NPC is more like a real human than a normal NPC.

TABLE VII
EVALUATION FOR NPC'S PERFORMANCE

No.	Questions
1	I think the emotional NPC is more interesting than the normal NPC.
2	I think the emotional verbal message of NPC is an interesting expression.
3	I prefer to choose emotional NPC as my teammate instead of normal NPC.
4	I think the emotional expression could help me to understand the NPC's status.

rules might mirror the inventors' emotion patterns well but not those of other people. For example, in WASABI, the emotion of fear is strictly located in the PAD space of (-80,80,100), and the emotion of sad is located in (-50,0,-100) for all people. Secondly, those models haven't considered real-time regulations by cognition. Comparing with existing models, CRAA could learn typical emotion patterns from human and perform an accurate knowledge retrieval based on Adaptive Resonance Theory.

We also conduct a questionnaire based experiment involving human users to evaluate our emotion model by comparing the emotional NPC with the non-emotional NPC. Two videos are recorded for emotional NPC and non-emotional NPC respectively in Unreal Tournament game. The human users are requested to answer the questionnaire after viewing the videos.

The questionnaire investigates the emotional NPC in three aspects: whether the NPC's emotion expression is correct; whether the emotional NPC is interesting and improves the game playability; and whether the emotional NPC is appealing and satisfies human users in game level. The questionnaire comprises three parts: Questions in Table VI are designed to evaluate the accuracy of our emotion model; questions in Table VII are designed to evaluate the playability/interesting of emotional NPC comparing with non-emotional NPC; questions in Table VIII are designed to evaluate the improvement of game performance with emotional NPC. For each of the questions, the answers are ranked from "strongly disagree" to "disagree", "neutral", "agree", and "strongly agree" with scaled values of 0.2, 0.4, 0.6, 0.8, and 1.0 respectively. Human users are supposed to answer these questions by choosing one of the optional answers.

The evaluation results are summarized in Table IX. Each result is calculated by averaging across the ten subjects (the same as before). We can observe that the emotional NPC obtains a decent value in accuracy showing that human users generally think the cognitive regulated emotions are appropriate, and the corresponding expressions are reasonable. The emotional NPC also obtains good results in terms of agent's performance and game level's performance, demonstrating that the emotional NPC is better and more popular than non-emotional NPC. By

TABLE VIII
EVALUATION FOR GAME'S PERFORMANCE

No.	*Questions*
1	The game with emotional NPCs gives me more fun.
2	I prefer to play the game with emotional NPC than without.
3	I feel more emotional when playing the game with emotional NPC.
4	The game with emotional NPC makes me fell more involved.
5	I feel a perceptual human-computer interaction in the game with emotional NPC.

TABLE IX
HUMAN USER EVALUATION RESULT

No.	*Emotion accuracy*	*Playability/interesting*	*Game level*
$meanscore$	0.87	0.91	0.90
$std.Dev$	0.08	0.10	0.08
max	1	1	1
min	0.80	0.40	0.60

broadcasting the NPC's affective status with expressive words, the cognitive emotional model could enhance the NPC in the aspects of human users interaction and improve the first person shooting game in terms of attractiveness and playability.

VI. CONCLUSION

Emotion modeling for virtual humans is a crucial component for computer games. Based on the cognitive regulated emotion theory and the network theory of emotion, this paper proposes a bio-inspired computational model called Cognitive Regulated Affective Architecture (CRAA) with a multi-layered architecture, in which the cognitive network, the appraisal layer and the affective network are designed to simulate the functions in prefrontal cortex (PFC), anterior cingulate cortex (ACC) and amygdala respectively. The above model has been examined in a first person shooting game showing good results in emotion simulation and game performance. Furthermore, the questionnaire based experiment also demonstrates the necessities of emotion modeling for NPC in games. Moving forward, we will focus on extending the CRAA by further enhancing the computational interactions between cognition and emotion.

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