Learning human emotion patterns for modeling virtual humans

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***Abstract*—Emotion modeling is a crucial part in modeling virtual humans. Although various emotion models have been proposed, most of them focus on designing specific appraisal rules. As there is no unified framework for emotional appraisal, the appraisal variables have to be defined beforehand and evaluated in a subjective way. In this paper, we propose an emotion model based on machine learning methods by taking the following position: an emotion model should mirror actual human emotion in the real world and connect tightly with human inner states, such as drives, motivations and personalities. Specifically, a self-organizing neural model called Emotional Appraisal Network (EAN) is used to learn from human being's emotion patterns, involving context, events, personality and emotion. Our experiments in a virtual world domain have shown that comparing with other emotion models, EAN has a much higher accuracy in emulating human emotion behaviour by learning from real human data.**

***Keywords*-emotion modeling; virtual human; self-organizing neural model**

I. Introduction

The modeling of humanoid agents in virtual environments is an attractive topic of investigation. Although it has, in the last decades, made much progress in terms of 3D graphical interfaces and high-fidelity sophisticated modeling of physical aspects, the modeling of intelligence aspects such as emotion and decisions are still limited.

In virtual spaces, each virtual human is essentially an autonomous agent, which is expected to function and adapt by themselves in a complex and dynamic environment [30]. The modeling of emotion could enrich virtual agents in abilities of expressing with lively facial expressions and behaviors, presenting motivated responses to environment, and intensifying their interactions with human users. For example, non-player characters with an emotion model could present interesting responses to environment [2] [25]. Also, interactive agents with an emotion model could form a better understanding of user's moods and preferences and can adapt itself to the user's needs [12]. As a result, emotion makes virtual agents human-like and appealing. Moreover, as emotion is indispensable in maintaining rational behaviors, a robust and accurate model of emotion-to-response relations is needed in modeling virtual humans.

Emotion modeling is not just about making agents emotional. In fact, emotion has an important role in human cognition. For human beings, emotion is indispensable in maintaining rational behaviors. It has been demonstrated by numerous experiments including functional magnetic resonance imaging (fMRI), electroencephalography (EEG), electromyography (EMG), and skin conductance (SC), that human emotion is significant in affecting human cognition [16], enhancing or impairing behavior performance [23], and guiding decision making [3]. People with brain damage change their judgment of emotion and distort normal behaviors. Furthermore, emotion modeling needs to consider individual's appraisal of environment. Appraisal theories [21] [27] [28] [24] claim that a person's emotion is his/her personal assessment of person-environment relationship based on events. Therefore, an emotion model needs to be integrated tightly with personal cognition, and other inner states, such as drives, motivations, and personalities. The objective behind this research is to empower virtual humans with the ability of emotional appraisal and coping while the environment changes. Therefore, two key issues are considered in this work. First, emotion model needs to mirror actual human emotions in the real world. Second, emotional appraisal should be specific to individuals and integrated with personal attributes, such as drives, motivations and personalities.

In the past years, many emotion models were proposed based on one or more psychological theories [21] [27] [28] such as EMA [19], FLAME [11], FAtiMA [9], WASABI [4], and PEACTIDM [17]. Most of them focused on designing appraisal parameters and IF-THEN rules to decide emotion instances. Depending on different application objectives, various appraisal mechanisms and variables are designed without a unified framework. In most models, emotion rules and variables have to be defined beforehand and their evaluation is often subjective. Furthermore, as the existing models were not derived through real human data statistically, they do not take into consideration the personal attributes.

This paper proposes an emotional appraisal network (EAN) based on Adaptive Resonance Theory (ART) [7], [8] and Pessoa's network theory of emotion [22]. The

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inputs to this emotion model include environmental context, the event that happens, and the personality of the individual. The context parameters and events are captured from the environment through perception, while personalities are designed based on the Openness-Conscientiousness-Extraversion-Agreeableness-Neuroticism (OCEAN) model [20]. More importantly, this model builds emotion rules by learning from real human data. Based on a self-organizing neural model called fusion ART [7], [8], the emotion model could learn different emotion patterns associated with different human personalities. We have compared our model with others in various benchmark experiments. Comparing with the existing rule based models, the EAN is more accurate in emulating human emotion and more appealing with its capability of learning and adaptation.

The rest of this paper is organized as follows. Section II reviews the recent related works. Section III reviews the network theory of emotion for human brain. Section IV introduces the personalized Emotional Appraisal Network (EAN) model. Section V presents empirical experiments and comparisons with related works. The final section concludes and discusses future work.

II. Related Works

Many computational emotion models have been proposed for designing virtual humans. El-Nasr *et al.* present FLAME based on the OCC model [21] and the "event-appraisal model" [24] [11]. 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. However, as FLAME is not designed for virtual humans but pets, it is not sufficient for simulating human emotions.

Marinier *et al.* [17] describe PEACTIDM, a computational structure to support emotional appraisal based on Scherer's theory [27]. Emotion is decided by six dimensions: suddenness, goal relevance, intrinsic pleasantness, conduciveness, control and power. The current emotion is determined according to how the six variables valued in their ranges. The variables and rules are defined and evaluated subjectively.

Marsella and Gratch [18] [19] build EMA based on EMILE [14] and 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 model is designed for mission rehearsal exercise training system, but does not consider personalities to emulate personalized human emotions.

Becker-Asano *et al.* [4] develop WASABI, which simulates appraisal processes based on the pleasure-arousal-dominance (PAD) space and Scherer's sequential-checking theory [27]. The three-dimensional emotion space describes all events in terms of three dimensions named pleasure (P), arousal (A) and dominance (D). By verifying the values of P, A and D, every emotion could be mapped into a specific location in the PAD space, by associating event evaluations with emotions. However, they utilize the PAD space values defined by Russell and Mehrebian [26] instead of learning from real data.

FAtiMA is proposed by Dias *et al.* [9] as a two-layered architecture to create virtual agents [1]. The concept of emotion in FAtiMA is based on the OCC theory [21]. Personality is integrated in FAtiMA for emotional expression and the other processes within cognition. 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.

III. 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 [22]. 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) [22] 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 such as personality 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.

IV. Emotional Appraisal Network

A. Design of EAN

The Emotional Appraisal Network (EAN) is proposed based on Adaptive Resonance Theory (ART) [7], [8] to learn the emotion association function of

$$E_m = f(S, E, P), \tag{1}$$

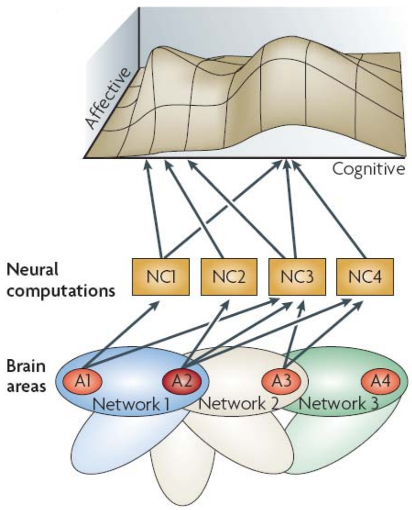

Figure 1. Pessoa's conceptual proposal of neural computations and emotion. (Adopted from [22])

where S, E, and P correspond to the input of current context states in which the agent is situated, the events that happened immediately, and human personalities respectively. The context and events are designed based on the specific environment of the agent, such as our Co-Space virtual campus [31]. On the other hand, personalities are designed based on the OCEAN model [20], which characterizes human personalities in five traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Personality defines a person's characteristics which influence his cognition and emotion. Although there are other personality models, such as Eysenck's two traits theory [13], Myers-Briggs-type indicator (MVTI) model [5], OCEAN is the one widely used in many areas, such as commercial recruitment, education and academic research. Therefore, in this work, OCEAN traits are adopted to characterize human personalities. Based on Pessoa's conceptual proposal of emotion (Figure 1), we design our emotion model by associating emotion with multiple modules and pathways, including the inner state, context, and perceptions, which are represented by human personalities, environmental state they are situated, and external events (shown in Figure 2).

Fusion ART learns cognitive nodes across multi-channel mappings simultaneously across multi-modal input patterns. By using competitive coding as the underlying adaptation principle, the network performs supervised learning to build the emotional appraisal system. Through code activation, code competition, template matching, template learning and code creation, EAN learns appraisal rules which map directly from context, events and personality to specific emotion instances. During performance, EAN senses the environment input, searches for the cognitive node which matches with the current context and event using the same code activation

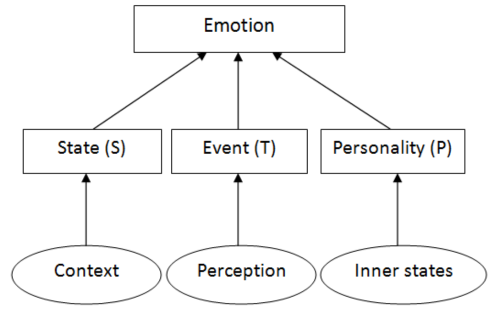

Figure 2. Conceptual framework for emotional appraisal.

and code competition processes. Upon selecting a winning node, the chosen node performs a readout of its weight vector into the emotion field, producing an emotion instance as output.

B. Fusion ART based emotion modeling

Fusion ART employs a multi-channel architecture (Figure 3), comprising a category field F_2 connected to a fixed number of (K) pattern channels or input fields through bidirectional conditionable pathways. The model unifies a number of network designs, most notably Adaptive Resonance Theory (ART) [7], [8], Adaptive Resonance Associative Map (ARAM) [29] and Fusion Architecture for Learning, COgnition, and Navigation (FALCON) [30], developed over the past decades for a wide range of functions and applications. The generic network dynamics of fusion ART, based on fuzzy ART operations [6], is summarized as follows.

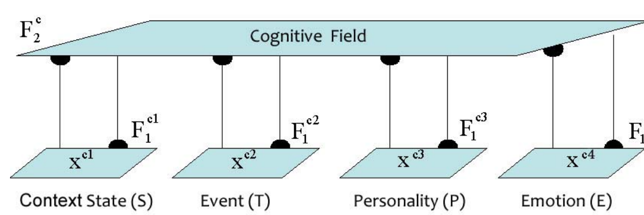

Figure 3. The neural model of EAN.

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 $\bar{I}_i^{ck} = 1 - I_i^{ck}$.
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 $k = 1, \ldots, K$.

As a natural extension of ART, fusion ART responds to incoming patterns in a continuous manner. It is important to note that at any point in time, fusion ART does not require input to be present in all the pattern channels. For those channels not receiving input, the input vectors are initialized to all 1s. The fusion ART pattern processing cycle comprises five key stages, namely code activation, code competition, activity readout, template matching, and template learning, as described below.

1) Emotion Learning: The fusion ART learns an emotion policy which maps directly from input patterns to desired actions. Given the state vector $\mathbf{S}$, event vector $\mathbf{E}$, personality vector $\mathbf{P}$, and emotion instance vector $\mathbf{E_m}$, the input vectors are set as $\mathbf{I}^{c1} = \mathbf{S}$, $\mathbf{I}^{c2} = \mathbf{E}$, $\mathbf{I}^{c3} = \mathbf{P}$ and $\mathbf{I}^{c3} = \mathbf{E_m}$. This model then performs code activation to select a category node J in the F_2^c field to learn the association between $\mathbf{S}$, $\mathbf{E}$, $\mathbf{P}$ and $\mathbf{E_m}$. 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:

$$T_j = \sum_{k=1}^{K} \gamma^{ck} \frac{|\mathbf{I}^{ck} \wedge \mathbf{w}_j^{ck}|}{\alpha^{ck} + |\mathbf{w}_j^{ck}|}, \tag{2}$$

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

$$T_J = \max\{T_j : \text{for all } F_2 \text{ node } j\}. \tag{3}$$

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

$$\mathbf{x}^{ck} = \mathbf{I}^{ck} \wedge \mathbf{w}_J^{ck}. \tag{4}$$

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:

$$m_J^{ck} = \frac{|\mathbf{I}^{ck} \wedge \mathbf{w}_J^{ck}|}{|\mathbf{I}^{ck}|} \geq \rho^{ck}. \tag{5}$$

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.

Table I
THE CONTEXT STATES IN CO-SPACE

No.	*State*
1	Walk on the way
2	Talk with people
3	Attend class
4	Engage in sports
5	Eating(or afternoon tea)
6	Self-study
7	Play

Template learning: Once a resonance occurs, for each channel ck, the weight vector $\mathbf{w}_J^{ck}$ is modified by the following learning rule:

$$\mathbf{w}_J^{ck(\text{new})} = (1 - \beta^{ck})\mathbf{w}_J^{ck(\text{old})} + \beta^{ck}(\mathbf{I}^{ck} \wedge \mathbf{w}_J^{ck(\text{old})}). \tag{6}$$

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.

2) Emotional Appraisal: Given the input state vector $\mathbf{S}$, event vector $\mathbf{E}$ and personality vector $\mathbf{P}$, the fusion ART model selects a category node J in the F_2^c field which determines the current emotion. For emotion decision, the input vectors $\mathbf{I^{c1}}$, $\mathbf{I^{c2}}$, $\mathbf{I^{c3}}$ and $\mathbf{I^{c4}}$ are initialized by $\mathbf{I}^{c1} = \mathbf{S}$, $\mathbf{I}^{c2} = \mathbf{E}$, $\mathbf{I}^{c3} = \mathbf{P}$, and $\mathbf{I}^{c4} = (1, ..., 1)$. The model then searches for the cognitive node which matches with the current input using the same code activation and code competition processes according to equations (2) and (3).

Upon selecting a winning F_2^c node J, the chosen node J performs a readout of its weight vector into the emotion field F_1^{c4} such that

$$\mathbf{x}^{c4} = \mathbf{I}^{c4} \wedge \mathbf{w}_J^{c4}. \tag{7}$$

The model then examines the output activities of the emotion vector $\mathbf{x}^{c4}$ and selects an emotion e_I, which has the highest activation value

$$x_I^{c4} = \max\{x_i^{c4} : \text{for all} \quad F_1^{c4} \quad \text{node} \quad i\}. \tag{8}$$

V. EXPERIMENTS

A. Virtual World Embodiment

One key objective of our work is to build a computational emotion mechanism which could mirror actual human

Table II
THE EVENTS IN CO-SPACE

No.	*Event*
1	Heard the news of quiz on tomorrow
2	Receive the broke up SMS from a friend
3	Receive the news that his favorite football team win
4	Heard the bad quiz result
5	Heard the good quiz result
6	Get hurt when walking or during sporting games
7	Pick up money on the road
8	Get a gift or voucher
9	The food is awful
10	The food is yummy
11	Provoked by a NPC or player (by player input)
12	Complimented by a NPC or player (by player input)

Table III
THE EMOTION SET (ADOPTED FROM [10])

No.	*Emotion*
1	anger
2	disgust
3	fear
4	happiness
5	sadness
6	Surprise

emotion in the real world. Here we briefly describe how the emotion model contributes to developing virtual humans in a 3D virtual world, called Co-Space [31]. Through 3D modeling and animation technologies, Co-Space simulates the campus world in terms of look-and-feel of the surrounding environment. Those virtual characters, not controlled by real human players but computer programmes, are called non-player characters (NPC). Each of them is embedded with perception and sensor modules, and could capture what has happened in their surrounding areas. There are many types of events in Co-space, such as the user-triggered events, which occur depending on the input from a human player; the environment events, controlled by environment agents, which occur depending on location or state; and the time-scheduled events, which are programmed for a specific NPC to engage in campus activities by following a certain schedule. NPC is supposed to show appropriate emotions when they encounter various events. Table I and Table II show the sample context states and events used in this work. The state attributes provide the context of events, and usually last for a longer time than events. On the contrary, an event occurs within a short time and happens during one of the states. The emotion set is designed by adopting Ekman's six basic emotions [10] (shown in Table III).

B. Experiment Methodology

The following experiments examine the EAN model in two aspects: whether EAN model could emulate human emotions correctly; and whether the emotion rules learned from limited human data could adapt to extended situations.

Table IV
SAMPLE EMOTION RULES

No.	*State*	*Event*	*Emotion*
1	Attend class	Receive a gift from friends	Happiness
2	Play	Heard the news of quiz on tomorrow	Fear
3	Eating	Pick up money	Surprise
4	Play	Provoked by other people	Disgust
5	Attend Class	Heard the bad quiz result	Sadness
6	Self-study	Get physical hurt	Anger

Human data is obtained by two questionnaires: the "Big Five Inventory" adopted from [15] for personality test, and the "Co-Space questionnaire", in which we list a set of situations that students may encounter in their campus life. Each situation is characterized by the happening of an event in Table I with a state context in Table II. Ten university students are involved in this experiment, including four females and six males. They are asked to complete the questionnaires with their own assessment of emotion, assuming they encounter these situations. Prior to the survey, we also provide them a short training in order to make them understand the questions. Thereafter, we create various emotion models for virtual humans based on the collected data, in which the data set for each subject contains 62 samples. The parameter setting used in EAN is as follows: choice parameter $\alpha^{ck} = 0.1$ for $k = 1...4$; learning rate parameter $\beta^{ck} = 0.1$ for $k = 1..4$; contribution parameter $\gamma^{c1} = \gamma^{c2} = \gamma^{c3} = 1$, $\gamma^{c4} = 0$; and vigilance parameter $\rho^{c1} = \rho^{c2} = \rho^{c3} = 0.9$, $\rho^{c4} = 1$. Each EAN is built with the inputs of context states, events and personalities, and the output of emotion instances. Table IV shows a sample set of the emotion rules elicited by learning from a subject who is characterized with "Agreeable" personality. We also examine the adaptability of EAN to extended situations (which do not appear in the training data), by using 61 samples to train and another one to test for individual subject. We obtain an average accuracy of 97.2 %, as shown in Table V, by averaging over 62 times across ten subjects. This result demonstrates that our model could learn subject's emotion patterns accurately and generalize them into extended cases.

C. Comparing with Other Models

We compare EAN with several recently proposed models, namely EMA [19], FAtiMA [9] and WASABI [4], as they provide clear and specific emotion appraisal rules. We adopt these models into our application and evaluate their accuracy using real human data. By taking a questionnaire-based approach, we replace their application scenarios with our states and events and ask the subjects (the same as in last section) 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

Table V
ACCURACY OF EAN AND OTHER MODELS

No.	*Model*	*Accuracy*
1	EMA	49.0%
2	FAtiMA	55.3%
3	WASABI	46.6%
4	EAN	97.2 %

experiments, we give the subjects a short training so that they understand these models correctly. The questionnaires list the same situations as in the last section, 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 examine whether the various emotion models could generate the correct emotion according to human data collected. For each model, the data set for each subject contains 62 samples, and we calculate the result for each model by taking average across ten subjects.

Table V shows the performance of EMA, FAtiMA, WASABI and EAN in terms of their prediction accuracy. Apart from EAN, most models achieve undesirable accuracy: 49.0% for EMA, 55.3% for FAtiMA, and 46.6% for WASABI. The low level of accuracy is due to their model's limitations by predefining the emotion rules subjectively. The predefined rules might mirror the inventors' emotion patterns well but not those of other people. For example, emotion appraisal in FAtiMA is decided by the evaluating variables of desirability, like relation and desirability for others. If "final desirability" is calculated as positive and "desirability for other" is positive, the emotion of happy is generated. Moreover, as individual's personalities are not considered, the rule-based emotion models are not suitable to mirror emotion of actual people with different personal traits. 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. These drawbacks may not be significant if we just want the virtual human to display some emotions to make them more interesting. However, a more challenging objective here is to emulate human emotion in the real world. In our application, as the virtual characters are expected to express believable emotions, it's necessary to model NPC's emotion patterns with human data. Our experiments results demonstrate that by learning from human data, the EAN model is more accurate than all other emotion models in emulating individual human emotion. This indicates that at least in our application, EAN is suitable and reliable to build emotional NPCs with different personalities, due to its high adaptability.

VI. CONCLUSION

This paper proposes a novel emotion model, known as the Emotional Appraisal Network (EAN), based on fusion Adaptive Resonance Theory. By learning from real human data, EAN can build robust emotion models for modeling realistic virtual humans in a virtual-reality world, called CoSpace. The EAN model, based on a 4-channel Fusion ART network architecture, has the properties of self-adaptation, generalization, and learning. Our questionnaire based experiments have shown that comparing with the existing models using generic emotion rules and variables, EAN is a far better choice for capturing and modeling human emotions. Moving forward, we aim to integrate the emotion model into an integrated cognitive architecture to create a more complete version of virtual humans.

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