Modelling Composite Emotions in Affective Agents

Xinjia Yu†, Chunyan Miao*†, Cyril Leung†‡ and Charles Thomas Salmon§

*School of Computer Engineering, Nanyang Technological University (NTU), Singapore

†Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly (LILY), NTU, Singapore

‡Department of Electrical and Computer Engineering, the University of British Columbia, Vancouver, BC, Canada

§Wee Kim Wee School of Communication and Information, NTU, Singapore

{xyu009, ascymiao}@ntu.edu.sg, cleung@ece.ubc.ca, salmon@ntu.edu.sg

***Abstract*—It is important for artificial agents to accurately infer human emotions in order to provide believable interactions. However, there is currently a lack of empirical results supporting affective agent to propose effective computational models for this purpose through analyzing individual profile information and the interaction outcomes. In this paper, we bridge this gap with a game-based empirical study. We propose a general model for interactions between an agent and a user in competitive game settings. Based on results from over 450 players in over 2,500 game sessions, we construct a regression model using a player's education level, age, gender and the interaction outcome as explanatory factors to compute his/her composite emotions consisting of the six basic emotions.**

***Keywords*-Affective computing; composite emotion;**

I. Introduction

Artificial agents are software entities designed to provide interactions to a person [1], [2], [3], [4]. They have been demonstrated to be useful in offering emotional companionship, building trust, and facilitating socialization [5], [6], [7], [8], [9], [10], [11]. One of the long term research objectives of human-agent interactions is to enable the agent to behaviour in human-like ways. The ability to demonstrate appropriate emotions is an important aspect of human-like agent behaviour.

In game-based environments infused with artificial agents such as [12], agents often need to formulate appropriate emotional responses. As hardware supporting facial expression-based emotion recognition (e.g., webcams, Kinect sensors) is not always available, agents need to infer players' emotional states based on each individual's characteristics from their profile information and the gameplay situations. However, there is a lack of actionable results from empirical studies.

In this paper, we bridge this important gap in the literature. We propose a general model for interactions between an agent and a user in competitive game settings. Based on a game with such settings, we conduct a large-scale study through an agent-based game involving over 450 players. Based on data collected from over 2,500 game sessions, we construct a regression model mapping players' characteristics and game outcomes to their self-reported mixed emotions which consist of Ekman's Six Basic Emotions [13].

II. The Game-based Study

In competitive game environments where players compete with artificial agents, many factors may affect the players' emotions. As it is not possible to exhaustively account for all game dependent factors, we focus on two categories of factors that are always present: 1) the players' individual characteristics, and 2) the interaction outcome. For individual characteristics, we select a 3-tuple $\langle \varepsilon_i, a_i, g_i \rangle$. $\varepsilon_i \in \{0, 1, 2, 3, 4, 5, 6\}$ is a player i's education level, where 6 = PhD, 5 = Master's, 4 = Bachelor's, 3 = Diploma, 2 = High School and 1 = Others. a_i is a player i's age. $g_i \in \{1, 2\}$ is a player i's gender, where 1 = Female and 2 = Male. For the interaction outcome, we select a 2-tuple $\langle s_i, s_{\text{AI}} \rangle$, where $s_i \in [0, 100]$ and $s_{\text{AI}} \in [0, 100]$ are the normalized scores for the player and the agent at the end of an interaction, respectively.

A game platform based on the above interaction model [14] was developed to conduct this study in which a player competes against an agent [15] to come up with efficient task allocation strategies. It contains an interactive tool that allows a player to express his/her current feeling in the form of mixture of the Ekman's Six Basic Emotions (i.e., Happiness, Sadness, Excitement, Boredom, Surprise and Anger) [13], and select how his/her facial expression would look like in the form of 2D smiley faces.

A. Regression Models

In order to produce actionable results that affective agent researchers can incorporate into their computational models, we propose a regression model relating the $\langle \varepsilon_i, a_i, g_i \rangle$ and $\langle s_i, s_{\text{AI}} \rangle$ to the strength of each of the six basic emotions as follows:

$$d_{(\text{Emotion})} = \beta_0^{(\text{Emotion})} + \beta_1^{(\text{Emotion})} \varepsilon_i + \beta_2^{(\text{Emotion})} a_i + \beta_3^{(\text{Emotion})} g_i + \beta_4^{(\text{Emotion})} s_i + \beta_5^{(\text{Emotion})} s_{\text{AI}} \tag{1}$$

where Emotion $\in$ {Happy, Sad, Excited, Bored, Surprised, Angry}. $d_{(\text{Emotion})} \in [0, 10]$ is the strength of a given emotion. In this model, we assume a player's education level, age, gender and the interaction outcome can be used as explanatory factors for the player's emotions.

Table I
REGRESSION ANALYSIS RESULTS

Emotion	$\beta_0^{(\text{Emotion})}$	$\beta_1^{(\text{Emotion})}$	$\beta_2^{(\text{Emotion})}$	$\beta_3^{(\text{Emotion})}$	$\beta_4^{(\text{Emotion})}$	$\beta_5^{(\text{Emotion})}$
Happy	3.169164***	0.106322	-0.07614***	1.098336***	0.036235***	-0.0218***
	(0.77653)	(0.067728)	(0.027694)	(0.152257)	(0.006622)	(0.006625)
Sad	4.915147***	0.279857***	-0.10809***	0.444615***	-0.04987***	0.026667***
	(0.669084)	(0.058356)	(0.023862)	(0.13119)	(0.005706)	(0.005708)
Excited	3.36115***	0.354395***	-0.18034***	0.799234***	0.019783***	-0.00166
	(0.718564)	(0.062672)	(0.025626)	(0.140892)	(0.006128)	(0.00613)
Bored	5.589433***	0.070521	-0.14543***	0.636569***	-0.03126***	0.018081***
	(0.69838)	(0.060912)	(0.024907)	(0.136934)	(0.005956)	(0.005958)
Surprised	2.630473***	0.423236***	-0.1521***	1.029228***	-0.0004	0.007397
	(0.709966)	(0.061922)	(0.02532)	(0.139206)	(0.006054)	(0.006057)
Angry	5.621244***	0.179757***	-0.15223***	0.368426***	-0.03448***	0.018173***
	(0.667734)	(0.058239)	(0.023814)	(0.130925)	(0.005694)	(0.005697)

Note: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$; standard errors are listed in the parentheses.

B. Analysis of Results

The game has been used by two universities in Singapore and China as part of the students' coursework. So far, 462 students have played the game through 2,683 sessions. Female players played 30.97% of the sessions and male players played 68.99% of the sessions. The majority of the players are between 20 to 30 years old with educational levels ranging from High School to Bachelor's degrees.

Through regression analysis, the results for the coefficient and intersection values for each basic emotion in the proposed regression models are shown in Table I. In summary, the regression results are in accordance with our assumption that $\langle \varepsilon_i, a_i, g_i \rangle$ and $\langle s_i, s_{\text{AI}} \rangle$ can be used as explanatory factors for the player's emotion expressed by the six basic emotions. Note that the results are only applicable to people from the specified backgrounds.

III. DISCUSSIONS AND FUTURE RESEARCH

In this paper, we contributed a regression model mapping the players' characteristics and player-agent interaction outcomes in competitive game settings into the six basic emotions. The results provides a basis for affective agents to compute the possible emotions for people from diverse background under different situations without having to analyze their facial expressions. In subsequent research, we plan to incorporate this model into companion agents in interactive games, and study the accuracy of the estimated user emotions based on judgements from real users.

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