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An Architecture for Personality-Based, Nonverbal Behavior in Affective Virtual Humanoid Character

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Abstract

As humans we perceive other humans as individually different based – amongst other things – on a consistent pattern of affect, cognition, and behavior. Here we propose a biologically and psychologically grounded cognitive architecture for the control of nonverbal behavior of a virtual humanoid character during dynamic interactions with human users. Key aspects of the internal states and overt behavior of the virtual character are modulated by high-level personality parameters derived from the scientific literature. The virtual character should behave naturally and consistently while responding dynamically to the environment's feedback. Our architecture strives to yield consistent patterns of behavior though personality traits that have a modulatory influence at different levels of the hierarchy. These factors affect on the one hand high-level components such as 'emotional reactions' and 'coping behavior', and on the other hand low-level parameters such as the 'speed of movements and repetition of gestures. Psychological data models are used as a reference to create a map between personality factors and patterns of behavior. We present a novel hybrid computational model that combines the control of discrete behavior of the virtual character moving through states of the interaction with continuous updates of the emotional state of the virtual character depending on feedback from interactions with the environment. To develop and evaluate the hybrid model, a testing scenario is proposed that is based on a turn-taking interaction between a human participant and a 3D representation of the humanoid character. We believe that our work contributes to individualized, and ultimately more believable humanoid artifacts that can be deploy in a wide range of application scenarios.

Keywords: Cognitive Architecture, Nonverbal behavior, Personality, BIS/BAS, Five Factor Model, Personality traits, Hybrid Model, Hierarchical Approach

1 Introduction

The term "personality" refers to consistent patterns of emotions, thinking and behavior, which make humans unique and distinguishable. During daily human to human interactions, people evaluate the personality of others e.g. to predict their behavior, to understand them, to help or to motivate them. One of the important sources of information people rely on when attributing personality to others is nonverbal behavior such as gestures, body stance, facial expressions, and gaze behavior. For instance,

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the speed of body movement or duration of direct gaze affects how people perceive personality of a person (Campbell & Rushton, 1978; Borkenau & Liebler, 1992). Likewise, during human and virtual humanoid character interaction, people attribute personality to virtual characters by using clues from their nonverbal behavior (e.g. McRorie et al., 2012). Yet, in many architectures designed for virtual humanoid characters, nonverbal behavior is generated for communication purposes and decision making processes while ignoring the importance of personality in the generation of behavior. This leads to virtual humanoid characters with behaviors that are not consistent through time and do not follow human behavioral patterns.

Our goal presented in this paper is to develop a biologically and psychologically grounded computational architecture for generating nonverbal behavior to express personality for virtual humanoid characters. The architecture is designed in a way which can generate plausible dynamic behavior for the virtual humanoid character in response to the human user's inputs in real time. Since we are focusing on nonverbal behavior of the virtual character, the interaction is "content-free" meaning there is no speech involved. Our problem domain is narrowed down to the turn-taking strategy-based interaction. In this study, the behavior that represents the personality include torso movements, head and neck movements, gaze, facial expressions, hand movements, body gestures and postures, all of which are visible from above the waist. For each behavior, we consider parameters like frequency and speed (e.g., frequency of blinking or speed of head movement). Gaze parameters such as fixation points and duration of gazing per points are also considered.

2 Computational Background on Expressing Personality through Nonverbal Behavior

Following is a review of related background literature on various computational models for generating the impression of emotion and personality through nonverbal behavior. Kshirsagar and Magnenat-Thalmann (2002) devised a personality model of emotional virtual characters. They used Bayesian Belief Networks and a layered approach for modeling personality, moods and emotions. The focus in this work was only on emotional personality. Alternatively, ALMA (A Layered Model of Affect) (Gebhard, 2005) was designed to provide a personality profile with real-time emotions and moods for virtual humanoid characters. Similarly, the concentration in this study was on modulating the appraisal process, but there was no mapping between nonverbal behavior and personality traits. Poznanski and Thagard (2005) developed a neural network model of personality and personality change. Their focus was on modeling personality changes, with nine behavior mapped to personality via output tags, e.g., "talk" or "avoid help". Similarly, Wen Poh et al. (2007) designed an architecture to control affective story characters with parameters for personality and emotion. They developed a hierarchical fuzzy rule-based system to control the body language of a story character with personality and affect. In this system, story designers specified a story context with personality and emotion values with which to drive the movements of the story characters. Zammitto et al. (2008) proposed a multidimensional hierarchical approach to model a parameterized facial character system, which only focused on facial features to express personality. Read et al. (2010) proposed a neural network model of structure and dynamics of personality based on research about the structure and neurobiology of human personality. Differences in the sensitivities of motivational systems and inhibitory strength were used to model the given personality traits. The model was designed only for high-level portions of behavior such as "Tease and Make Fun of" and "Ask for Date" as well as for situational parameters such as "At Home" or "In Conference Room". McRorie et al.'s work (2012) was part of a European project (SEMAINE) with the aim of developing a system that facilitates human interaction with conversational and Sensitive Artificial Listeners (SAL). Their main focus was the content of the conversation and behavior during the conversation. The study empirically examined how users rate videos and images of virtual humanoid characters' expressive behavior, but no real-time interaction between humans and the virtual character was tested. In another study, Lim et al. (2012) developed architecture for affective virtual characters, using a biologically-inspired theory of human action regulation. In their work, personality was mainly revealed to modulate emotional framework and the appraisal process.

Each of the previously mentioned approaches concentrated on a few high level parameters (e.g. emotional changes or content of the dialogue) or segments of behavior such as 'Ask for Date' to express personality. Our model is a comprehensive approach that addresses high level parameters such as emotion and coping in conjunction with low level realization of personality through nonverbal behavior. In the model, logical turn-taking behavior is synced with continuous emotional reaction of the virtual character and all presented to user in terms of gestures and facial expressions. Another aspect offered by our model which is missing in most of mentioned models is possibility of real-time interaction between user and virtual character. Real-time interaction provides strong infrastructure for perceiving personality of the virtual character. Interacting dynamically with a virtual character that is able to express unique personality, creates a rich and affective experience for users and adds to the virtual character's believability.

3 Approach

3.1 Bio-Psychological Approach to Personality

Personality is the pattern of characteristic thoughts, feelings, and behavior that distinguish one person from another and persists over time and situations (Pervin et al., 2005). Different theories on personality models have emerged by considering the effects of variables like individual differences, the environment, varying situations, mental skills, and intelligence levels. Gray's bio-psychological personality model suggests that people differ in the sensitivity of their Behavioral Approach System (BAS, responsible for impulsivity) or Behavioral Inhibition System (BIS, responsible for anxiety) (Gray, 1987). People with high BAS are sensitive to signals of reward and desired events, while those with high BIS tend to be more sensitive to moving away from unpleasant events and punishments. Wiggins's (2003) model conceptualizes personality as a circumplex along the two axes of Affiliation, and Dominance. The Five Factor Model of personality (FFM) is a comprehensive model that is widely used and validated in several studies (McCrae & John, 1992). In the Five Factor Model, personality is categorized according to the following traits: openness to experience (inventive/curious vs. consistent/cautious), conscientiousness (efficient/organized vs. easy-going/careless), extraversion (outgoing/energetic vs. solitary/reserved), agreeableness (friendly/compassionate vs. cold/unkind), and neuroticism (sensitive/nervous vs. secure/confident). Extraversion and neuroticism factors are mapped to BIS and BAS in Gray's bio-psychological model of personality (Gray, 1987). While extraversion reflects how outgoing and social a person is, neuroticism describes the level of emotional instability and the tendency to experience negative emotions, such as stress and depression.

3.2 Personality and Differences in Affect, Cognition, and Behavior

Personality traits are related to emotional and cognitive processing (Kumari et al., 2004). Personality traits reveal themselves in several aspects. First of all, they affect the gestures, facial expressions and postures. For instance, people scoring high in extraversion have extensive smiling (Borkenau & Liebler, 1992). They show more gesturing, more head nods, and faster general speed of movement (Borkenau & Liebler, 1992). Based on Campbell and Rushton's study, people with high score in neuroticism are associated with touching oneself, and an absence of expressive gestures (Campbell & Rushton, 1978). Highly anxious people generate significantly more stroking, twitches, and tremors. Secondly, people with different personalities tend to filter their emotions differently. For example, people who score high in extraversion tend to express their feelings more easily as they do less filtering. Thirdly, personality traits affect the emotional experience. In general, extraversion is correlated with positive emotions when neuroticism is correlated with negative emotionality (Costa and McCrae, 1980). Neuroticism is correlated with showing signs of tension or anxiety and express insecurity or sensitivity, hostility, self-pity, and guilt. Based on Eysenck's biological theory of personality (Eysenck, 1994), people scoring high in neuroticism show strong reaction to emotionally arousing experiences. In addition, it takes more time for them to return to pre-arousal states. Alternatively, people who are scored high in extraversion have lower baseline levels of cortical arousal. Thus, they tolerate higher levels of arousal (Hagemann et al, 2009). On the contrary, people with low score in extraversion withdraw to avoid further increases in arousal which they find difficult to withstand (Eysenck, 1994). Personality is also revealed through the coping mechanisms and emotional reactions of the virtual characters to users' behavior. In coping situations, extraversion is correlated with showing positive thinking and rational actions while neurotics show passiveness and indecisiveness (McCrae & Costa, 1986).

3.3 Proposed Architecture for Personality-based Control of Nonverbal Behavior

Our cognitive architecture implements biologically grounded personality traits of extraversion and neuroticism. In our proposed architecture, personality traits have a modulatory influence at four levels: 1) Personality parameters affect the generation of non-verbal behavior such as gestures. As a result, low level parameters such as speed of the movements and expressed facial expression are affected by personality. We take into account the semiotics of communicative elements including indexical (pointing), iconic (describing) and symbolic (conventional) signs. 2) Different personalities affect the level of filtering of emotions. Not all the internal emotions are revealed through facial expressions to users. 3) Different personality parameters affect the coping behavior of the virtual character. For instance, introvert virtual character behaves more passively in coping situations. 4) Personality affects emotional reactions of the virtual character. For instance, as mentioned before, people with high score in neuroticism experience more negative emotions in general. Our proposed hybrid model consists of two main components being an "Emotionally-Continuous" system and an "Event-based" system (Figure 1). In conjunction, the Emotionally-Continuous system and the Event-based system generate the gestures, postures and facial expressions that are expressing personality. The Event-based component generates the virtual character's communicative gestures based on different states of the interaction and the user's behavior. The Event-based system is responsible for the logic and flow of the interaction. It determines which gestures should be generated based on rules and configuration parameters defined at the beginning or during the interaction and goals and strategies specified for the virtual character. Because of the discrete and turn-based nature of Event-based system, this component is implemented using the finite state machine (FSM) (Selic et al., 1994). A state machine is a set of input events, output events and states. The machine can change from one state to another (which is called transition) when an event or condition is triggered. FSM controls the turn-taking behavior of the interaction. In addition, in FSM, specific events or information triggers corresponding gestures from the virtual character. For instance, if the virtual character wants to guide the user to move to a place, he points to the location and gazes at the user to encourage him. Our coping mechanism is a part of Event-based system. Coping is a mechanism of dealing with problems while trying to minimize the conflict. The effectiveness of a coping mechanism depends on the individual's personality (Lazarus & Folkman, 1984). Extraverts' cognitive response to stressors is to think positively and react rationally, while neuroticism is correlated with withhold and being passive in coping situations.

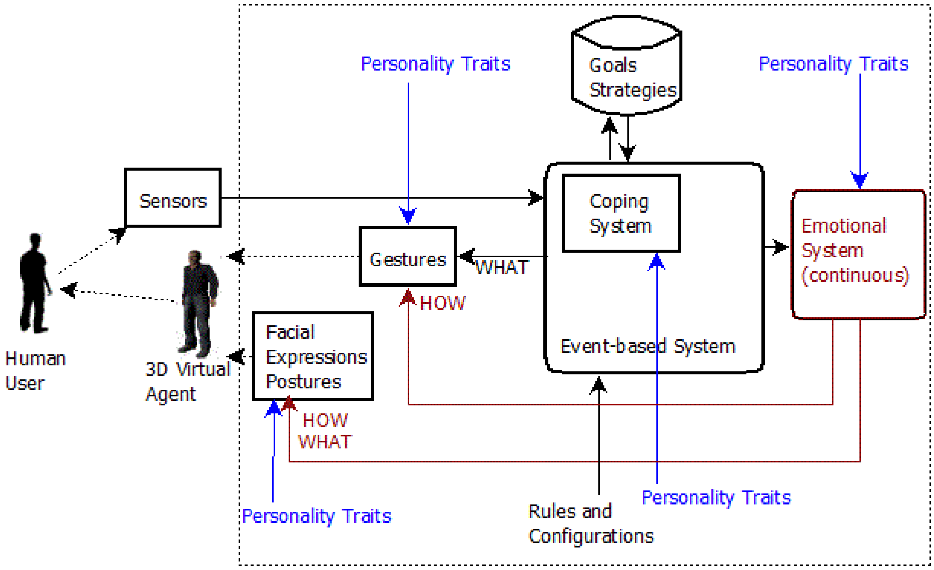

Figure 1 – Structure of the proposed hybrid architecture for real-time interaction between a human participant and a virtual character. Personality traits have a modulatory effect at four levels of the hierarchy: 1) Gestures e.g. extraversion is correlated with showing faster hand and head movements; 2) Facial expressions e.g. extroverts filter less and show more facial emotions; 3) Coping mechanism e.g. coping

The virtual character's facial expressions are controlled by the Emotionally-Continuous component. Opposite to communicative gestures, which are triggered when an environmental event is triggered, emotions are continuously updated based on internal and outside status. The emotional weights of the gestures are also specified by the Emotionally-Continuous component. The system continuously calculates the emotion by comparing the virtual character's goals with inputs such as the user's actions. Russell's Circumplex model of emotion with two axes of valence (displeasure-pleasure) and arousal (relaxation-excitation) is used (Russell, 1980). Emotional valence and arousal are continuously changing based on how much time is passed being in a specific state. For instance, if the virtual character is continuously receiving negative feedbacks from the environment, his disappointment can continue to increase. If the virtual character cannot find a way to avoid the negative feedback, after a certain amount of time, he/she may start finding a way to cope with this situation. Based on the personality of the virtual character, some of the emotions are filtered and considered as internal emotional states, and some are shown to the users. Generated values of valence and arousal in the Emotionally-Continuous System is mapped to Ekman's Action Coding System to generate facial expressions for the virtual character (Ekman, 1977). The combination of gestures, facial expressions and postures are fed to the animation toolkit continuously and are presented to the user during interaction. The inputs of the model are continuously received from sensors installed in the environment. The virtual character reacts dynamically and in real-time to these inputs. Parameters of the system are 'personality parameters' and 'configurations and rules' which are set at the beginning of the interaction are input parameters. These configurations rules are specific to the scenario of the interaction, such as the desired coordination of the user in the environment. Goals and strategies of the interaction are hard-coded in the first version of the model to narrow the study. The outputs of the model are facial expressions, postures and gestures of the virtual humanoid character, which are dynamically generated and fed to the animation toolkit to be displayed to the user.

We propose to compute the valence (V) and arousal (A) in the Emotionally-Continuous System according to the following formulas:

$$V(t) = V(t_0) + L_v(t) + F_v(t)$$
$$A(t) = A(t_0) + L_a(t) + F_a(t)$$

$V(t_0)$ and $A(t_0)$ are the initial valence and initial arousal values, $L_v(t)$ and $L_a(t)$ are the convergence of valence and arousal to a constant amount over time; and F_v and F_a are the effects of stimuli on the emotional experiences (Schweitzer & Garcia D, 2010). Personality is considered as four cases: high-extraversion, low-extraversion, high-neuroticism and low-neuroticism. According to psychological theories, people score higher in neuroticism tend to show stronger response to negative stimuli (Eysenck, 1994). We employ an exponential decay function to formalize the speed of emotional changes in response to a stimulus: $F_V(t) = F_V(t-1)\ e^{dR*t}$, and $F_a(t) = F_a(t-1)\ e^{dR*t}$. The decay-rate (dR) is specified to be higher in the high-neuroticism compared to the low-neuroticism case to reflect faster emotional change in response to stimuli. To accommodate for psychological data showing that people with higher score in neuroticism experience more negative emotion in general (Costa and McCrae, 1980), we set the initial value $V(t_0)$. People who score high in extraversion tolerate higher levels of arousal while people with a low score in extraversion withdraw to avoid further increases in arousal (Eysenck, 1994; Hagemann et al, 2009). To address this fact, in each step, $F_a(t)$ is only calculated if $F_a(t-1) < arousalThreshold$ where $arousalThreshold$ is higher in the case of high-extraversion than for the low-extraversion one. The values of the emotional state are converging over time to a higher value for high-extraversion than low-extraversion and low-neuroticism than high-neuroticism by calculating constant amounts A_{ss} and V_{ss} using: $L_a(t) = A_{ss} - ((A_{ss} - L_a(t-1))e^{-dR*t})$, and $L_V(t) = V_{ss} - ((V_{ss} - L_V(t-1))e^{-dR*t})$.

3.4 Model Implementation

The inputs of our system are 'location of the user' and 'height of the user'. Users' locations are captured with an overhead camera. Height of the user is captured using a Microsoft Kinect 3D camera and is used to locate user's head where virtual character gazes at. The two main components of the system, 'Event-based' and 'Emotionally-Continuous', are implemented using Simulink/Matlab. Sensor information is fed to the Event-based system. Parameters of the system (e.g. 'personality traits') are fed to the system at the beginning or dynamically through the interaction using a graphical user interface. Smartbody (Shapiro, 2011) an academic 3D character animation toolkit developed at the University of Southern California's ITC lab is used as our animation rendering system which provides locomotion, gazing and nonverbal behavior in real time under our scripted control via the Behavior Markup Language (Kopp et al., 2006). Future Work and Conclusion

3.5 Empirical Testing in Real Time Interaction

To truly evaluate how users perceive the personality of virtual humanoid character based on their nonverbal behavior, a real-time interaction between the user and the virtual character with focus on nonverbal behavior is required. Here we propose a test case scenario for evaluating the personality model, with the goal of creating an easy-to-learn and engaging scenario that provides an interactive environment with minimum conversation. Our testing paradigm is a scenario of an interactive game between a user and a virtual humanoid character. During this game the user's objective is to reach a target specified on the ground. The virtual character tries to guide the user using gestures such as pointing (indexical) and symbolic signs (e.g. head node and head shake). The user can choose to trust the virtual character and follow the guides or ignore the virtual character's directions. The user wins the game if she reaches the target. After or during the interaction users will rank the personality of the virtual character using the TIFI personality test. Results will be compared with parameters specified before the experiment. We designed a prototype in which we recorded the interaction of two humans instead of a virtual humanoid character and a human. The recorded human behavior were analyzed and used as a reference for generating the virtual humanoid characters' nonverbal behavior.

3.6 Summary and Conclusion

Consistency and coherence in behavior are key concepts for creating virtual characters which follow the behavior patterns of humans. Explicitly endowing virtual characters with a personality individualizes them by ensuring they exhibit consistent behavior (Wang & Mckenzie, 1998). We propose a computational model to generate perception of personality through nonverbal behavior of a virtual character during dynamic interactions with human users. A hierarchical hybrid model is designed which combines logical behavior and continuous updates of the emotional expressions of the virtual character while encapsulate different layers of the system. Two main component of the system Emotionally-Continuous system and the Event-based system in conjunction generate the gestures and facial expressions that express personality. The Event-based system is responsible for the logic and flow of the interaction and generates the virtual character's communicative gestures based on different states of the interaction and the user's behavior. Emotionally-Continuous system is continuously updated and controls the virtual character's facial expressions. The system continuously calculates the emotion by comparing the virtual character's goals with inputs such as the user's actions. In proposed model personality traits have an influence at four levels: 1) At generation of non-verbal behavior 2) At the level of filtering of emotions. 3) At the coping behavior of the virtual character. 4) At the emotional reactions of the virtual character. Different aspects of our model can be extended and enriched in future. Right now the inputs from the environment are limited to user's coordination and height. Our system has the possibility to feed more channels of inputs from the environment such as noises and light changes. Being responsive to users' gestures and emotions also enriches the experience. Another future step is to increase the graphical quality of the virtual humanoid character's representation and generated animations via high end facial expressions, animation and rendering. We hope increasing the quality of interaction between human and virtual humanoid characters lead to the wider use of virtual characters in various faculties such as educational systems, therapy systems, games, training systems, museum guides, story-telling and interactive dramas.

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