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Abstract. Realism and plausibility of computer controlled entities in entertainment software have been enhanced by adding both static personalities and dynamic emotions. Here a generic model is introduced which allows the transfer of findings from real-life personality studies to a computational model. This information is used for decision making. The introduction of dynamic event-based emotions enables adaptive behavior patterns. The advantages of this new model have been validated with a four-way crossroad in a traffic simulation. Driving agents using the introduced model enhanced by dynamics were compared to agents based on static personality profiles and simple rule-based behavior. It has been shown that adding an adaptive dynamic factor to agents improves perceivable plausibility and realism. It also supports coping with extreme situations in a fair and understandable way.

1 Introduction

While graphic fidelity continues to increase steadily, entertainment software often suffers from unrealistic and incomprehensible behavior of computer controlled entities (called agents). An obvious example for such behavior are agents that are expected to walk to a specific location but instead run into a wall. Another example is repetitive and predictable behavior created by using simple rule-based agents. When modeling large groups of entities, like pedestrians in a crowded street, using simple agents may be acceptable and even necessary to keep the required computation for decision making on a viable level. While modeling a small number of agents which are expected to be in the focus of a users attention, these agents have to make plausible decisions to display behavior with a high degree of realism. In gaming applications incorrect behavior may be annoying but tolerable, and predictability might even be desired, both can be counterproductive in other cases, e.g. serious training or learning applications.

Personality profiles can potentially increase the realism and as such the level of immersion achieved by an application. A new generic model for mapping personality studies and profiles to a standardized form for use in software applications is suggested. This will allow utilization of real life studies for modeling behavior of autonomously interacting agents. Adding personality to an agent makes briefly observed decisions appear more consistent and therefore more realistic. Observing a single agent for an extended period of time however still reveals implausible behavior, because it does not adapt to its environment. In a deterministic system a static personality would always lead to the same action when in the same situation. When a user observes agents experiencing events, that are expected to invoke emotions, these agents are expected to adapt their behavior. For example, when observing pedestrians at a road, they might wait for cars to pass, because they consider the observed gaps as too small to safely cross the street. After waiting for some time, some of them might lose their patience and run across the street with a gap they would not have accepted previously. To add this aspect, a new model for adding emotions to agents is introduced, enabling adaptive behavior.

2 Related Work

Modeling personality and emotion is an integral part in the field of virtual humans and affective agents research. These types of entities are employed for a wide variety of applications, e.g. digital storytelling [1], human-computer interaction [2], education [3, 4], and entertainment [5]. In the majority of cases a user observes and/or interacts with a specific virtual presence over a prolonged time span; perhaps even across multiple sessions. Creating believable agents in such applications requires (a) consistent behavior based on a personality [6] and (b) the ability to convey emotions through the agent's expressions and decisions.

Trying to understand why people take the actions and make the decisions they do, many studies were performed to find correlations between their personality and performance in specific tasks (e.g. [7], [8], [9]). By integrating personality profiles into the decision making processes of an agent, they can be utilized to model more plausible and realistic behavior (e.g. deadlock handling in traffic [10]). Because of differences in the cognitive processes, the way personality influences the performance of a person is highly dependent on the specific task [7]. To model personality for virtual humans the Five Factor Model (FFM) is most commonly used [11]. The model's descriptive nature and the fact that only five personality traits are sufficient to define a personality are likely responsible for its popularity (cf. [3]). Previous work in our research group also identified the FFM as a useful tool for agent development in the context of a road safety education application [12, 13]. But even within one model, different scales for each trait exist, e.g. NEO Five Factor Inventory [14], Big Five Questionnaire [15]. This again encourages the development of a generic model for computational use of personality profiles.

In case of emotions, the OCC model [16] seems to be the method of choice for many researchers (cf. [11, 17]). The model includes 22 types of emotions that can be either positive or negative. However, its scale makes the model complex [18] and depending on the application there are alternatives for representing emotions. For example, Curran defined a model that requires only eight dimensions [19]. PANAS reduces this number even further by only considering positive and negative affect [20].

3 Modeling Adaptive Behavior

To model adaptive behavior of agents this approach enhances those in two steps: First, a personality will be added to each agent to distinguish them from each other and provide means for creating a consistent behavior pattern. Secondly, a dynamic emotion model will be added to enable adapting to events in the environment. While the term "emotion" has been used a few times already, it is ambiguous and thus needs to be defined for the remainder of this work. In popular language emotions are often equated to mood. However, it is distinguished as described by Thayer in [21]: Mood describes a lasting state of feeling born of complex cognitive processes with often unknown antecedents, in comparison emotions, as used in this contribution, are short lived feelings directly caused by that experience. Therefore, our model of emotions are caused by predefined events, influence the behavior for a limited period of time, and regress until normal behavior, as defined by the personality, is restored.

3.1 Personality Profile Model

If incorporated in the decision making processes, personality profiles associated to agents can make their behavior more persistent. While arbitrary personality profiles might be considered as sufficient for this, creating the profiles from real life studies enables utilizing further studies linking personalities to specific behavior patterns (e.g. driving behavior [8]). This way the agents can not only be persistent, but also simulate realistic behavior patterns. To achieve this, a model is introduced to represent complete personality studies independent of the personality model used as a source for personality profiles. After that a conceptual example for the use of personality profiles in decision making processes is shown.

$$
\begin{aligned}
&\mathbf{p} = \langle p_1, \ldots, p_n \rangle \in \mathbb{R}^n \\
&P = \{p_0, \ldots, p_k\} \subseteq \mathbb{R}^n \\
&\mathcal{P} = \mathrm{P}(P) \setminus \emptyset \\
&D = \{\mathrm{d}_1, \ldots, \mathrm{d}_n\}, \forall\, \mathrm{d} \in D : \mathrm{d} : \mathbb{R}^n \to \mathbb{R}
\end{aligned}
\tag{1}
$$

Formal Description. As mentioned above, there are many models for describing personalities with varying number of dimensions to which the personality is mapped. To be as generic as possible the use of any number of dimensions is supported. In (1) a personality profile $\mathbf{p}$ is described as a sequence of numbers p_1 to p_n each describing the value of a single dimension. For ease of use for each dimension 1 to n is made accessible by functions d_1 to d_n from a set D.

Furthermore, a finite set of profiles is denoted as P and the power set P of P without the empty set is denoted as $\mathcal{P}$.

$$\mathrm{avg} : \mathcal{P} \times D \to \mathbb{R}, \qquad (P, \mathrm{d}) \mapsto \frac{\sum_{\mathbf{p} \in P} \mathrm{d}(\mathbf{p})}{|P|} \tag{2}$$

$$\mathrm{stdDev} : \mathcal{P} \times D \to \mathbb{R}, \qquad (P, \mathrm{d}) \mapsto \sqrt{\frac{\sum_{\mathbf{p} \in P} \left(\mathrm{d}(\mathbf{p}) - \mathrm{avg}\,(P, d)\right)^2}{|P|}} \tag{3}$$

$$\mathrm{zScore} : \mathbb{R}^n \times \mathcal{P} \times D \to \mathbb{R}, \quad (\mathbf{p}, P, \mathrm{d}) \mapsto \frac{d\,(\mathbf{p}) - \mathrm{avg}\,(P, \mathrm{d})}{\mathrm{stdDev}\,(P, \mathrm{d})} \tag{4}$$

Using the average value $\mathrm{avg}(P, \mathrm{d})$ of a dimension d over all profiles $\mathbf{p}$ in a set P from equation (2) and the standard deviation $\mathrm{stdDev}(P, \mathrm{d})$ of the same variables from equation (3) the equation (4) calculates the z-score for a single dimension d of a personality profile $\mathbf{p}$ in reference to a set of personality profiles P. Note that $\mathbf{p}$ does not have to be inside the set P. The z-score is an important measurement for this model, as it provides a relative measurement in reference to the average, making relative comparison between values viable, independent of the used personality study.

After describing the formal basics needed for modeling single and sets of personality profiles, in the next step a comprehensive model for entire personality study results is introduced in equation (5). According to this definition a Study $\mathcal{S}$ consists of a set of personality profiles P containing all the profiles $\mathbf{p}_0$ to $\mathbf{p}_n$ that have been compiled from the subjects. Additionally a set K of classifications of profiles is part of the study. Such a class $\mathcal{K} \in K$ consists of a single personality profile $\mathbf{p}$ representing the class, the tuple of z-scores of that profile $\mathbf{z}$ and a set of personality profiles $Q \subseteq P$ bundling the profiles $\mathbf{p} \in P$ that are associated with this class. These classifications categorize the large set of profiles in a much smaller set while preserving the identifying properties of those profiles. Techniques to identify such classifications for a set of profiles aren't subject to this contribution and already exist in the literature (e.g. Herzberg and Roth [22]). Furthermore, l and h represent the minimum and maximum values a dimension is theoretically able to achieve in the given study (e.g. NEO-FFI: 0 to 48).

$$\begin{aligned}
&\mathcal{S} = \langle P, K, l, h \rangle \text{ with} \\
&P = \{\mathbf{p}_0, \ldots \mathbf{p}_n\}, \mathbf{p_0} \text{ to } \mathbf{p_n} \text{ are the profiles compiled from study } \mathcal{S} \\
&\mathcal{K} = \langle Q, \mathbf{p}, \mathbf{z} \rangle, \text{ with} \\
&\quad Q \subseteq P, \forall\, \mathrm{d} \in D : l \leq \mathrm{d}(\mathbf{p}) \leq h \wedge \mathrm{d}(\mathbf{z}) = \mathrm{zScore}(\mathbf{p}, P, \mathrm{d}) \\
&K = \{\mathcal{K}_0, \ldots, \mathcal{K}_m\}, \text{ with } \bigcup_{\mathcal{K}_i \in K} Q_i \subseteq P \\
&l, h \in \mathbb{R}, \forall\, \mathrm{d} \in D \wedge \forall \mathbf{q} \in P : l \leq \mathrm{d}(\mathbf{q}) \leq h
\end{aligned} \tag{5}$$

Utilizing the Model for Decision Making. How to use this model in a computer application to make more plausible decisions depends strongly on the data provided by studies. Orientating the integration in decision making processes on the given information is essential for plausible and persistent agent behavior.

For example a study from Herzberg in [8] validates an assumed correlation between three classes of personality profiles and driving behavior. By either creating profiles from the prototypes of those classes with minor random variations, or using real profiles from studies and mapping them to these classes, a set of personality profiles can be designed for assignment to autonomously behaving agents.

For the decision making itself one option would then be that those agents would take the mapping of their personality profile to personality classes into account when making decisions. Another option would be to look at the defining prototypes of those classes and having the decision making be based on distinct features (e.g. their overall combination of high, low and medium values in the different dimensions of the profile). The first option is far from a continuous distinction because of the limited differences in the deciding factor. Whereas the second option gives potential continuous distinction for decision making, it is usually overly complex and thus hard to implement and prone to errors.

Therefore, it is recommended to consolidate the numerous dimensions of a personality profile into a single number. The function for this transformation depends strongly on the study used to correlate personality to an agents behavior. In the given example from Herzberg one classification is interpreted as aggressive, one as careful and one as something in between. With that a continuous function is designed that maps the prototype profile of the first class to a low value, the second to a high value and the third to a value in the middle. With such functions, each agent gains a single continuous parameter derived from his personality that can be integrated into the decision process according to the findings of the used study, and lessen the problems of the two options described.

3.2 Modeling Emotions

The next step is to add a dynamic component to the model in the form of emotions. It is introduced in four steps: Representing, perceiving, fading emotions and influencing behavior. Emotions will affect the behavior by temporarily influencing the personality profile. Similar to personality profiles an emotional state is represented in multiple dimensions. The given model will utilize a two dimensional approach of positive and negative emotions. Those are used because of the following reasons: They are accessible, comprehensible and most events causing emotional changes can be mapped to those intuitively. They provide enough utility while keeping the complexity moderate. However, the model can be adjusted to utilize any number of emotional dimensions if desirable.

Representing Emotions. To represent a single emotion and make its fading configurable, unlike a dimension of personality profiles, in equation (6) a dimension of emotional states is defined as a tuple. The value of d_1 here denotes the current value of the emotion. The other three values d_2, d_3 and d_4 are for controlling the fading. By storing the variables to control the fading into each dimension of emotions they may differ for each dimension (e.g. positive emotions may regress faster than negative ones). The base value d_2 is used as a reference point for fading and denotes the value from which the fading started. The parameter for the linear part of the fading d_3 is used to quantify the rate of reduction a single fading step performs. Lastly, the parameter for the exponential part of the fading d_4 controls the time the current value stays almost exactly the same before starting to be reduced. For convenience, functions for accessing the distinct parts are provided with the definition.

$$\begin{aligned}\mathbf{d} = \langle d_1, d_2, d_3, d_4 \rangle \in \mathbb{R}^4 \text{ with } 0 \leq d_3 \leq 1 \\ \text{current} : \mathbb{R}^4 \to \mathbb{R}, (\mathbf{d}) \mapsto d_1 \\ \text{base} : \mathbb{R}^4 \to \mathbb{R}, (\mathbf{d}) \mapsto d_2 \\ \text{linF} : \mathbb{R}^4 \to \mathbb{R}, (\mathbf{d}) \mapsto d_3 \\ \text{expF} : \mathbb{R}^4 \to \mathbb{R}, (\mathbf{d}) \mapsto d_4\end{aligned} \tag{6}$$

A function for setting $\mathbf{d}$ from definition (6) to a new value is required. With $\text{set}(\mathbf{d}, v)$ in equation (7) setting $\mathbf{d}$ to a new value v sets $\text{current}(\mathbf{d})$ and $\text{base}(\mathbf{d})$ to v, while preserving the parameters $\text{linF}(\mathbf{d})$ and $\text{expF}(\mathbf{d})$.

$$\text{set} : \mathbb{R}^4 \times \mathbb{R} \to \mathbb{R}^4, (\mathbf{d}, v) \mapsto \langle v, v, \text{linF}(\mathbf{d}), \text{expF}(\mathbf{d}) \rangle \tag{7}$$

An emotional state is constructed as a tuple of dimensions $\mathbf{d}$ from (6). Definition (8) shows the two-dimensional emotional state $\mathcal{E}$ as applied in this contribution. Like D for personality profiles, E consolidates functions for accessing specific dimensions of an emotional state. Here $\text{ne}(\mathcal{E})$ denotes the negative emotions, whereas $\text{pe}(\mathcal{E})$ denotes the positive ones. It has to be noted that with this setup the emotional dimensions are independent from each other. This allows one to construct the influence emotions have on the behavior for each dimension separately. For example when modifying a personality based on the FFM, negative emotion could make agents more neurotic, while positive do not make them less neurotic, but more agreeable.

$$\begin{aligned}&\mathcal{E} = \langle \mathbf{d}_1, \mathbf{d}_2 \rangle \in \mathbb{R}^4 \times \mathbb{R}^4 \\ &E = \{\text{ne}_\text{e}, \text{pe}_\text{e}\} \text{ with} \\ &\quad \text{ne} : \mathbb{R}^4 \times \mathbb{R}^4 \to \mathbb{R}^4, \mathcal{E} \mapsto \mathbf{d}_1, \quad \text{pe} : \mathbb{R}^4 \times \mathbb{R}^4 \to \mathbb{R}^4, \mathcal{E} \mapsto \mathbf{d}_2\end{aligned} \tag{8}$$

Perceiving Emotions. Emotions are experienced by an agent when involved into an incident defined as emotionally relevant by the application. In this model perception of an emotion is modeled as the modification of the current emotional state of an agent controlled by the experienced emotions described as an incident $\mathbf{i}$ defined in equation (9). It has the same number of elements as dimensions of emotions, containing one numeric value for each dimension to be perceived when it is experienced by an agent. Again functions are provided for easy access to the values of negative emotion $\text{ni}(\mathbf{i})$ and positive emotion $\text{pi}(\mathbf{i})$.

$$\begin{aligned}&\mathbf{i} = \langle i_1, i_2 \rangle \in \mathbb{R}^2 \\ &\text{ni} : \mathbb{R}^2 \to \mathbb{R}, (\mathbf{i}) \mapsto i_1, \quad \text{pi} : \mathbb{R}^2 \to \mathbb{R}, (\mathbf{i}) \mapsto i_2\end{aligned} \tag{9}$$

The perception of such an incident is influenced by the personality profile of the perceiving agent. As intuitively assumed and also implied by the dimension neuroticism as emotional stability (see John and Srivastava [23]) studies found correlations between the personality of persons and their proneness to perceiving specific emotions (e.g. see Watson and Clark [24]). With this in mind the perception in this model is a function incorporating the personality and graveness of the incident. To set which dimension of a personality influences which emotional dimension how strong, in equation (10) a n-tuple is introduced for each dimension. Here n is the number of personality dimensions used.

$$\mathbf{s}_{ne} = \langle s_1, \cdots, s_n \rangle \in \mathbb{R}^n, \quad \mathbf{s}_{pe} = \langle s_1, \cdots, s_n \rangle \in \mathbb{R}^n \tag{10}$$

with equation (10) it is possible that certain combinations of personality $\mathbf{p}$, tuple $\mathbf{s}_{ne}$ and tuple $\mathbf{s}_{pe}$ lead to negative perceptions (e.g. an experienced incident with $\mathrm{ni}(\mathbf{i}) > 0$ lowers the negative emotion $\mathrm{ne}(\mathcal{E})$ instead of increasing it). Therefore two additional parameters l_i and c_i are introduced in definition (11). The value l_i denotes what minimum percentage of any incident $\mathbf{i}$ will be perceived. And c_i denotes a global scalar for perceiving emotions providing a tool for calibrating the values generated by this model.

$$l_i \in \mathbb{R} \text{ with } 0 < l_i \leq 1, \quad c_i \in \mathbb{R} \text{ with } 0 < c_i \tag{11}$$

In equation (12) $\mathrm{perceive}(a, \mathbf{i})$ updates the emotional state $\mathcal{E}_a^T$ of an agent a from the set of existing agents A according to the occurring incident $\mathbf{i}$ by creating a new emotional state $\mathcal{E}_a^{T+1}$. Whereas the new value of emotional dimensions $\mathrm{ne}\left(\mathcal{E}_a^{T+1}\right) / \mathrm{pe}\left(\mathcal{E}_a^{T+1}\right)$ are set to the value of the old states $\mathrm{ne}\left(\mathcal{E}_a^{T}\right) / \mathrm{pe}\left(\mathcal{E}_a^{T}\right)$ increased by the maximum of the percentage of the given emotion of $\mathbf{i}$ as set by l_i and the sum of influence the personality realizes as set by the tuples $\mathbf{s}_{ne}$ and $\mathbf{s}_{pe}$.

$$\begin{aligned}
\mathrm{perceive} : A \times \mathbb{R}^2 \rightarrow \mathbb{R}^4 \times \mathbb{R}^4, (a, \mathbf{i}) = \mathcal{E}_a^{T+1} \text{ with} \\
\mathrm{ne}\left(\mathcal{E}_a^{T+1}\right) &= \mathrm{set}\left(\mathrm{ne}\left(\mathcal{E}_a^{T}\right), \mathrm{current}\left(\mathrm{ne}\left(\mathcal{E}_a^{T}\right)\right) + \max\{l_{ne}, c_{ne}\}\right) \\
l_{ne} &= l_i \cdot \mathrm{ni}\left(\mathbf{i}\right) \\
c_{ne} &= c_i \cdot \mathrm{ni}\left(\mathbf{i}\right) \cdot \sum\nolimits_{\mathrm{d} \in D} \mathrm{d}\left(\mathbf{s}_{ne}\right) \cdot \mathrm{d}\left(\mathbf{p}_a\right) \\
\mathrm{pe}\left(\mathcal{E}_a^{T+1}\right) &= \mathrm{set}\left(\mathrm{pe}\left(\mathcal{E}_a^{T}\right), \mathrm{current}\left(\mathrm{pe}\left(\mathcal{E}_a^{T}\right)\right) + \max\{l_{pe}, c_{pe}\}\right) \\
l_{pe} &= l_i \cdot \mathrm{pi}\left(\mathbf{i}\right) \\
c_{pe} &= c_i \cdot \mathrm{pi}\left(\mathbf{i}\right) \cdot \sum\nolimits_{\mathrm{d} \in D} \mathrm{d}\left(\mathbf{s}_{pe}\right) \cdot \mathrm{d}\left(\mathbf{p}_a\right)
\end{aligned} \tag{12}$$

Fading of Emotions. As this model handles emotions as short lived feelings rising as a direct reaction to experiences, they also have to fade away over time. To achieve that, a fading function will be called in a small interval (e.g. one second) to regress the emotional state step by step, starting when no incident $\mathbf{i}$ was experienced in the last time step. The function, as shown in (13), takes a single emotional dimension $\mathbf{d}^T$ and creates a new one $\mathbf{d}^{T+1}$ for the next time step keeping all fading parameters the same, only changing the current value. This new value is set to the maximum of zero, the linear fading function $\mathrm{lin}(\mathbf{d}^T)$ and the exponential function $\exp(\mathbf{d}^T)$.

$$
\begin{aligned}
\mathrm{fade} : \mathbb{R}^4 \to \mathbb{R}^4, \left(\mathbf{d}^T\right) &\mapsto \mathbf{d}^{T+1} = \left\langle d_1, \mathrm{base}\left(\mathbf{d}^T\right), \mathrm{linF}\left(\mathbf{d}^T\right), \mathrm{expF}\left(\mathbf{d}^T\right)\right\rangle \\
\mathrm{current}\left(\mathbf{d}^{T+1}\right) &= d_1 = \max\left\{0, \mathrm{lin}\left(\mathbf{d}^T\right), \exp\left(\mathbf{d}^T\right)\right\} \\
\exp : \mathbb{R}^4 \to \mathbb{R}, (\mathbf{d}) &\mapsto \frac{\mathrm{current}\left(\mathbf{d}\right)^2}{\mathrm{base}\left(\mathbf{d}\right) + 10^{-\mathrm{expF}(\mathbf{d})}} \\
\mathrm{lin} : \mathbb{R}^4 \to \mathbb{R}, (\mathbf{d}) &\mapsto \mathrm{current}\left(\mathbf{d}\right) - \mathrm{linF}\left(\mathbf{d}\right)
\end{aligned}
\tag{13}
$$

Figure 1 shows some exemplary fading curves for some different emotional dimensions $\mathbf{d}_1$ to $\mathbf{d}_4$ to give a better understanding of this rather complex function. The linear function simply subtracts the provided parameter linF from the current value, reducing it linearly over time. In the beginning the exponential function reduces the value slowly, because $\mathrm{current}(\mathbf{d})$ and $\mathrm{base}(\mathbf{d})$ start the fading at the same value (see $\mathrm{set}(\mathbf{d}, v)$ in (7)), keeping the value nearly the same level for a period of time determined by expF. While the numerator keeps getting smaller with each call of $\mathrm{fade}(\mathbf{d})$, the denominator stays the same until $\mathrm{set}(\mathbf{d})$ is called again, which effectively resets the fading to start anew. When $\mathrm{current}(\mathbf{d})$ gets small enough that $\exp(\mathbf{d})$ reduces it more than $\mathrm{lin}(\mathbf{d})$ the linear function takes over the fading, operating as a break to assure a steady change in the behavior.

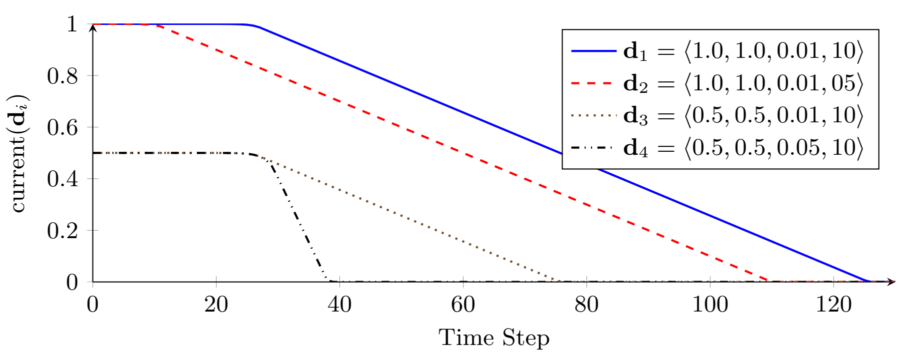


Fig. 1: Fadings of emotions starting at values from $\mathbf{d}_1$ to $\mathbf{d}_4$. $\mathbf{d}_2$ starts linear fading earlier because of a lower value of $expF(\mathbf{d}_2)$. $\mathbf{d}_4$ fades the fastest because of the highest value of $linF(\mathbf{d}_4)$. $\mathbf{d}_1$ and $\mathbf{d}_3$ start linear fading at the same time and proceed parallel, even though $\mathbf{d}_3$ starts with a lower value.

Utilizing Emotions. To utilize this model of emotions for influencing the behavior, a function is introduced to affect a personality profile from section 3.1. As these profiles already influence the behavior, it is not necessary to change the decision making process again. Also by having them seamlessly integrated in the personality profiles, emotions can be switched on and off dependent on the application's need. So the influence of incidents that change the emotional state is modeled as temporary influences on personality profiles.

The way in which emotions affect a personality profile is described with n-tuples, where n is the number of dimensions of the personality model used. For each dimension of emotion one tuple has to be created. In this case these are the two n-tuples $\mathbf{t}_{ne}$ and $\mathbf{t}_{pe}$ in (14). The values in each n-tuple are coefficients for the current value of the corresponding emotion. Whereas the values $\mathrm{d}(\mathbf{t}_{ne})$ and $\mathrm{d}(\mathbf{t}_{pe})$ are used for calculating the affect on the value of the personality dimension $\mathrm{d}(\mathbf{p})$.

$$\mathbf{t}_{ne} = \langle t_1, \cdots, t_n \rangle \in \mathbb{R}^n, \quad \mathbf{t}_{pe} = \langle t_1, \cdots, t_n \rangle \in \mathbb{R}^n \tag{14}$$

A limited-id-function $\mathrm{lid}(x, l, h)$ is introduced in (15) to keep the result for each personality dimension inside the bounds defined for the used study. It takes a value x, a minimum l and a maximum h. The result of this function is the value x if it is inside the given boundaries, else the result is the exceeded boundary l or h.

$$\mathrm{lid} : \mathbb{R} \times \mathbb{R} \times \mathbb{R} \to \mathbb{R}, (x, l, h) \mapsto \begin{cases} l, & \text{for} \quad x < l \\ h, & \text{for} \quad x > h \\ x, & \text{for} \quad \mathit{else} \end{cases} \tag{15}$$

Transforming the static personality profile $\mathbf{p}_a$ of an agent a into an dynamic profile $\mathbf{b}_a$ influenced by emotions is done with equation (16). For each dimension d of the personality profile the dynamic value $\mathrm{d}(\mathbf{b}_a)$ is determined by taking the static value $\mathrm{d}(\mathbf{p}_a)$ and adding each emotion dimension multiplied by the corresponding value of the tuples from definition (14). As this can cause values outside the boundaries set by the personality study the lid-function is used to limit the result to valid values. The resulting dynamic $\mathbf{b}_a$ is structural identical to the static $\mathbf{p}_a$ and can be used analogous to it everywhere in the application.

$$\begin{aligned} &\mathbf{b}_a = \langle b_1, \cdots, b_n \rangle \in \mathbb{R}^n \text{ with} \\ &\quad \forall\, \mathrm{d} \in D : \mathrm{d}\left(\mathbf{b}_a\right) = \mathrm{lid}\left(\mathrm{d}\left(\mathbf{p}_a\right) + \mathrm{n}\left(\mathcal{E}_a, d\right) + \mathrm{p}\left(\mathcal{E}_a, d\right), l, h\right), \quad l, h \in \mathcal{S} \\ &\quad \mathrm{n} : \mathbb{R}^4 \times \mathbb{R}^4 \times D \to \mathbb{R}, (\mathcal{E}, \mathrm{d}) \mapsto \mathrm{current}\left(\mathrm{ne}\left(\mathcal{E}\right)\right) \cdot \mathrm{d}\left(\mathbf{t}_{ne}\right) \\ &\quad \mathrm{p} : \mathbb{R}^4 \times \mathbb{R}^4 \times D \to \mathbb{R}, (\mathcal{E}, \mathrm{d}) \mapsto \mathrm{current}\left(\mathrm{pe}\left(\mathcal{E}\right)\right) \cdot \mathrm{d}\left(\mathbf{t}_{pe}\right) \end{aligned} \tag{16}$$

4 Evaluation Scenario: Unregulated Crossroad

To evaluate the models of dynamic personality profiles and emotions, they were applied to the specific scenario of an unregulated crossroad with the priority-to-the-right system in effect. Problems may occur as soon as agents arrive at the crossroad from at least three sides at the same time. In that case a circular dependency graph can arise, indicating a deadlock. Figure 2 illustrates the case of four agents arriving at the same time.

4.1 Parameterization of the Personality and Emotions Model

For the generation of personality profiles the study from Herzberg and Roth [22] was used. It provides a categorization of personalities based on a profound

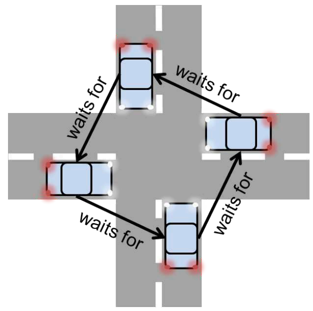


Fig. 2: Deadlock situation on an unregulated four-way crossroad. If four agents arrive at the same time at all roads there is no rule to resolve this deadlock situation.

study of over 1500 subjects. Furthermore, the three classes "Resilient", "Overcontrolled" and "Undercontrolled" are used in another study from Herzberg [8], connecting them to driver behavior which is used to model the decision process. Only provided with the z-scores the bounds for those studies are unknown. Therefore, the assumption was made that the highest z-score may be increased by 10% without stepping over the boundaries imposed by the used questionnaire. The values of the given z-scores in [22] are relatively small (-1.5 to 1.5). Since the z-scores are measured in units of standard deviation, creating or dynamically modifying profiles with values that exceed the highest given scores by 10% should result in profile values within the unknown bounds of the study. Additionally, the range was normalized to -1 to 1. Profiles for agents will be created by taking one of the personality prototypes connected to driving behavior by Herzberg (undercontrolled, overcontrolled, resilient) [8] and randomly modifying each dimension by 10%.

To simplify the integration of a 5-dimensional profile into the decision making process, the factor "politeness" φ is introduced. It is used for decision processes, like Kesting et al. did for the lane change model MOBIL [25]. However, rather than taking an arbitrary value, in our case it is derived from the personality profile. Equation (17) is defined based on the Herzberg's findings in [8] and [22]. For the default profiles of the used classes this function results in a low value of politeness φ of 0.22 for undercontrolled, a medium value of 0.45 for overcontrolled and a high value of 0.75 for resilient agents. The coefficients in $\mathbf{c}$ correspond to the personality dimensions, stating that the politeness φ dependends to 80% on agreeableness and to 20% on conscientiousness. Besides producing values that are consistent with the findings of Herzberg, they also represent an intuitive connection between politeness and personality.

$$\varphi = \mathrm{lid}\left(\frac{\left(\sum_{\mathbf{d}\in D}(\mathrm{d}(\mathbf{c})+\mathrm{d}(\mathbf{p}))+1\right)}{2}, 0, 1\right), \quad \mathbf{c} = \langle 0, 0, 0, 0.8, 0.2\rangle \tag{17}$$

The first parameters for emotions to be set are the ones for the fading. With $\mathrm{linReg}(\mathbf{d}) = 0.1$ and $\mathrm{expReg}(\mathbf{d}) = 1$ agents are set to forget emotions very fast, thus making them emulate new drivers, free of previous stress, each time they arrive at the crossroad. Positive emotion may intuitively be invoked when one agent lets another go. But these emotions would only take effect after crossing the intersection and fade away before arriving at there once more. Thus for this specific scenario only negative emotions, experienced while waiting at the crossroad, will be configured.

To describe the correlation between experiencing emotions and the personality, values from the studies by Watson and Clark 1992 in [24] were applied to $\mathbf{s}_{ne}$. They found that out of the five dimensions of the FFM only neuroticism influences the perception of negative emotions. Taking these findings into account the parameters were set to $\mathbf{s}_{ne} = \langle 0.341, 0, 0, 0, 0 \rangle$. Further perception parameters were set to $l_i = 0.1$ and $c_i = 0.5$ leading to a minimum perceived emotion of 10% of the value defined by the emotion event and a global reduction of perception of 50%.

The effect of negative emotion was set to $\mathbf{t}_{ne} = \langle 1, 0, -0.1, -0.75, -0.3 \rangle$. These values are based on the definition of the personality dimensions and personal experience. With this parameterization, negative emotions promote neuroticism (which in return promotes perception of negative emotion); openness decreases slightly, agreeableness decreases significantly and conscientiousness decreases moderately.

4.2 Road Network Setup

The road network is set up as a closed system as shown in Figure 3. At the beginning a specified number of agents is randomly distributed across the network of roughly 2 km (two loops of 500 m with two driving directions). The maximum velocity was set to 50 km/h. Assuming a constant velocity while driving, agents have about 35 seconds for emotion effects to fade between departure and arrival at the crossroad. The time step for perceiving and regressing emotion was set to one second.

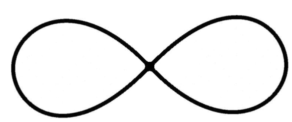


Fig. 3: Layout of the road used for the test scenario. Every agent leaving the crossroad in the center will reach it again after a distance of approximately 500 meters.

Three behavioral types of agents were considered separately: Strictly rule-based (RB), static personality-based (PB) and dynamic emotion-based (EB) agents. The RB agents will strictly follow the applicable traffic rules. When detecting a deadlock the PB and EB agents will utilize their personality profiles through the politeness factor φ to decide which of the involved agents will take action to resolve the deadlock. The involved agent with the highest politeness will give way to the agent waiting to its left, resolving the circular dependency graph. Additionally, the EB agents will react to waiting times by perceiving it as incidents creating negative emotion. When waiting to cross, they perceive an “emotion incident” $\mathbf{i}_1 = \langle 0.2, 0 \rangle$ during each time step.

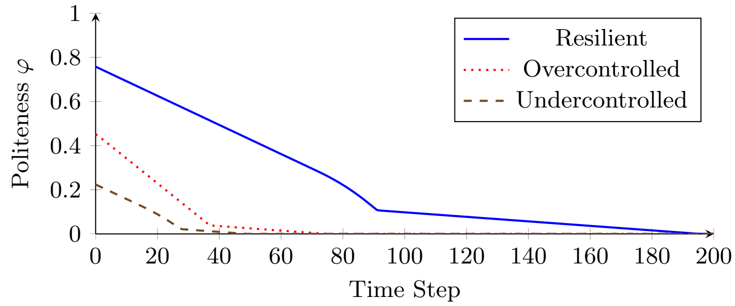


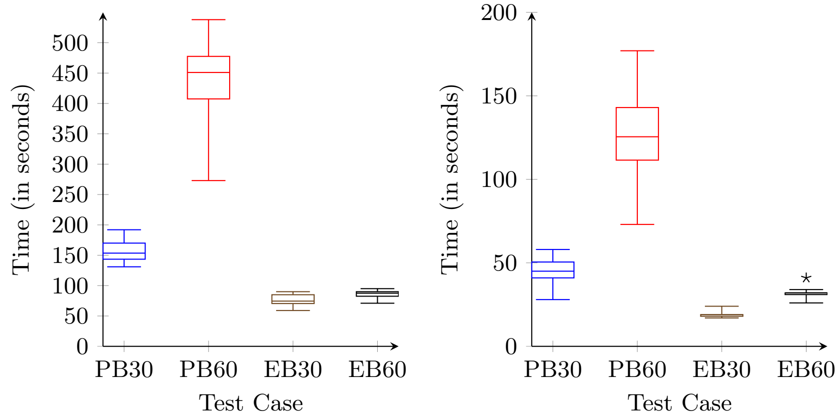
Fig. 4: Progression of the politeness φ for each personality prototype when perceiving incidents for waiting as first in line. The politeness decreases with increasing waiting time depending on the personality profile.

Figure 4 shows the progression of the politeness φ of the class prototypes of agents when waiting as first in line at the crossroad. For the evaluation each agent type was simulated for 60 minutes with 30 and 60 agents randomly distributed across the road network. Each combination of type and number of agents was computed ten times.

5 Results and Discussion

The behavior of RB agents showed similar patterns to the results reported in [10]. With these agents deadlocks occurred in every single run within only a few minutes, decreasing the flow on the road to zero. Thus, the results of the RB agents will no longer be considered here. Instead focus will be on the PB and EB agents.

Figure 5 (a) shows the maximum times a single agent had to wait as first in line at the crossroad for each test run. It illustrates that waiting times for EB agents were limited to more plausible values than for PB agents. During each test run at least one of the PB agents waited at the crossroad for about 2.5 minutes when simulating 30 agents and up to 8 minutes when simulating 60 agents. In contrast none of the EB agents waited more than 1.5 minutes. In addition, figure 5 (b) depicts the average times of agents waiting as first in line at the crossroad for each test run demonstrating that the maximum values are not outliers. Taking both graphs into account, waiting times of PB agents are overall longer than those of the EB agents. Despite their static profiles, the PB agents' waiting times vary strongly depending on initial position on the road and routing choices at the crossroad. By dynamically adapting the personalities and thus their behavior, EB agents show more consistent results over the different test runs. The adaptation handles the situation so well that even doubling the number of agents from 30 to 60 barely changes waiting times. In comparison, the waiting times of up to 8 minutes with 60 PB agents as shown in Figure 5 (a) are very implausible.



(a) (b)

Fig. 5: (a) Maximum waiting time of a single agent over all test runs and configurations. (b) Average waiting time of all agents over all test runs and configurations.

The reason for the difference in behavior can be identified when looking at the distribution of yields performed by the agents in Figure 6. Each yield was performed by one of the agents to resolve an identified deadlock. The graph shows the number of yields per agent performed in one test run. For clarification agents were sorted by their personality prototype. Within every scenario the structure of the results was very similar throughout all runs, therefore a single run was chosen for each scenario configuration (PB 30, EB 30, PB 60, EB 60) as a representative.

Consistent over all scenarios is the fact that resilient agents perform by far the most yields to resolve a deadlock. Only in rare cases do over- or under-controlled drivers yield. These results are consistent with our interpretations of Herzberg's findings from [8]. The reason for the long waiting times of PB agents is that there is always one particular agent, from the group of resilient drivers, that yields too often while others barely yield at all. For the chosen examples the agent with the most yields for the PB 30 configuration performed 25% and for the PB 60 configuration 40% of all yields. However, for the EB agents yields were distributed considerably more evenly between the agents with a resilient personality. In the displayed EB 30 configuration, the agent with the most yields performed about 11% and in the EB 60 configuration 6% of all yields. In comparison, in an ideal distribution each of the 10 (20) resilient agents of the EB 30 (EB 60) configuration would perform 10% (5%) of all yields.

An additional factor to judge the plausibility of the behavior is the number of consecutive yields of an agent. A driver that willingly increases his/her waiting time by yielding to another driver in a deadlock situation, would be expected to do so only a few times before running out of patience. For all runs of the EB configurations the highest number of consecutive yields was 2 or 3, which is reasonable. In contrast, consecutive yields recorded in the PB configurations

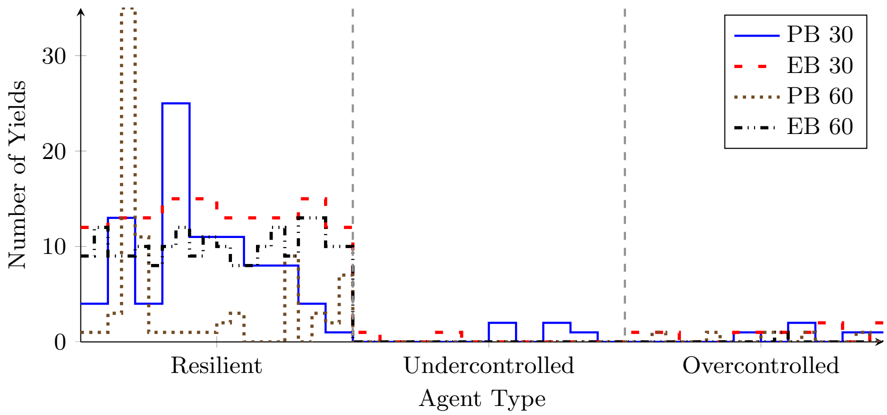


Fig. 6: Yields per agent of one exemplary test run per scenario (PB 30, EB 30, PB 60, EB 60). Agents are sorted by personality prototype.

were between 5 and 7 for 30 agents and between 8 and 19 for 60 agents. These numbers indicate implausible behavior and at the same time explain the higher waiting times for PB agents as well as show the improvement achieved by EB agents.

6 Conclusion and Future Work

In this contribution we built on previous work presented in [10] arguing that adding personality profiles to agents and utilizing them in their decision making process results in more plausible observable behavior. Furthermore, a new model has been introduced to map personality studies to a uniform structure for efficient use in computer applications making the distribution of profiles and the corresponding behavior more realistic. To further improve upon the integration of static personality profiles, an emotion model was integrated to allow for adaptive behavior. By adding the emotion model to a background layer, the complexity of the decision making process remains unchanged.

To evaluate the proposed models, a generic traffic simulation scenario consisting of a four-way crossroad with the priority-to-the-right system in effect has been applied. The integration of a personality profile to agents that otherwise strictly follow traffic rules was confirmed to be an advantage for the specified traffic scenario. While rule based acting agents were not able to resolve the occurring deadlock, agents with static as well as dynamic personality profiles were able to cope with the situation, but showed different behavior in problem solving. When simulating agents with static profiles the “most polite” agent ended up waiving its right of way multiple times in a row in order to resolve the situation. This behavior resulted in prolonged waiting times, which observers would consider implausible. By introducing negative emotions caused by waiting at the crossroad, the agent’s emotional state changed and in turn decreased its politeness. Thus, while simulating agents with dynamic profiles, deadlock resolving yields were evenly distributed across agents of the *resilient* category; the group with the "most polite" drivers. The results showed more plausible behavior by preventing consecutive yields by a single agent and unrealistic waiting times for that agent.

While the presented models create more plausible behavior in the given application scenario, proving that the behavior is also realistic requires the comparison to real traffic data. So far we do not have access to such type of data in any form. As a possible solution to this issue, subjects could provide this data by completing reference tasks in a driving simulator. Additionally, further evaluations are necessary to show that the same positive results can be observed for other scenarios; also those not related to road traffic. Finally, the introduced methodology is to be integrated into the established FIVIS [12] project to improve road safety training for bicycle riders.

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References

[1] Rank, S., Petta, P.: Backstory authoring for affective agents. In: Interactive Storytelling. Volume 7648 of Lecture Notes in Computer Science. Springer Berlin Heidelberg (2012) 144–149

[2] Kiselev, A., Hacker, B., Wankerl, T., Abdikeev, N., Nishida, T.: Toward incorporating emotions with rationality into a communicative virtual agent. AI & SOCIETY **26**(3) (2011) 275–289

[3] André, E., Klesen, M., Gebhard, P., Allen, S., Rist, T.: Affective interactions. Springer-Verlag New York, Inc., New York, NY, USA (2000) 150–165

[4] Lester, J.C., Towns, S.G., Callaway, C.B., Voerman, J.L., FitzGerald, P.J.: Embodied conversational agents. MIT Press, Cambridge, MA, USA (2000) 123–154

[5] Signoretti, A., Feitosa, A., Campos, A., Canuto, A., Fialho, S.: Increasing the eciency of npcs using a focus of attention based on emotions and personality. In: 2010 Brazilian Sym. on Games and Dig. Ent. (SBGAMES). (2010) 171–181

[6] Ortony, A.: On Making Believable Emotional Agents Believable. In: Emotions In Humans And Artifacts. MIT Press (2003)

[7] Matthews, G., Davies, D.R., Westerman, S.J., Stammers, R.B.: Individual differences: Personality and Mood. In: Human Performance: Cognition, Stress, and Individual Differences. Psychology Press (2000) 265–285

[8] Herzberg, P.Y.: Beyond accident-proneness: Using Five-Factor Model prototypes to predict driving behavior. J. of Research in Personality **43**(6) (Dec. 2009) 1096–1100

[9] Lauriola, M., Levin, I.P.: Personality traits and risky decision-making in a controlled experimental task: An exploratory study. Personality and Individual Differences **31**(2) (2001) 215–226
[10] Seele, S., Herpers, R., Becker, P., Bauckhage, C.: Cognitive Agents for Microscopic Traffic Simulations in Virtual Environments. In: International Conference on Entertainment Computing. (2012) 1–8
[11] Zerrin Kasap, N.M.T.: Intelligent virtual humans with autonomy and personality: State-of-the-art. Intelligent Decision Technologies **1**(1-2) (2007) 3–15
[12] Herpers, Rainer, e.a.: Multimedia Sensory Cue Processing in the FIVIS Simulation Environment. In: Multiple Sensorial Media Advances and Applications: New Developments in MulSeMedia. IGI Global (2012) 217–233
[13] Kutz, M., Herpers, R.: Urban traffic simulation for games: a general approach for simulation of urban actors. In: Proc. of the 2008 Conf. on Future Play: Research, Play, Share. Future Play '08, New York, NY, USA, ACM (2008) 181–184
[14] Costa, P.T., McCrae, R.R.: Revised NEO Personality Inventory (NEO PI-R) and NEO Five-Factor Inventory (NEO FFI): Professional Manual. Psychological Assessment Resources (1992)
[15] Caprara, G.V., Barbaranelli, C., Borgogni, L., Perugini, M.: The big five questionnaire?: A new questionnaire to assess the five factor model. Personality and Individual Differences **15**(3) (1993) 281 – 288
[16] Mehrabian, A.: Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology **14**(4) (1996) 261–292
[17] Bressane Neto, A., Corra da Silva, F.: On the construction of synthetic characters with personality and emotion. In Rocha Costa, A., Vicari, R., Tonidandel, F., eds.: Advances in Artificial Intelligence SBIA 2010. Volume 6404 of Lecture Notes in Computer Science. Springer Berlin Heidelberg (2011) 102–111
[18] Bartneck, C.: Integrating the occ model of emotions in embodied characters. In: Workshop on Virtual Conversational Characters, Citeseer (2002)
[19] Curran, J.P., Cattell, R.B.: The eight state questionnaire. Technical report, The Institute for Personality and Ability Testing, Champaign, Illinois (1975)
[20] Watson, D., Clark, L.A., Tellegen, A.: Development and validation of brief measures of positive and negative affect: the PANAS scales. Journal of personality and social psychology **54**(6) (June 1988) 1063–70
[21] Thayer, R.E.: Modern Perspectives on Mood. Oxford University Press, New York, USA (1989)
[22] Herzberg, P.Y., Roth, M.: Beyond resilients, undercontrollers, and overcontrollers? an extension of personality prototype research. European Journal of Personality **20**(1) (January 2006) 5–28
[23] John, O.P., Srivastava, S.: The big five trait taxonomy: History, measurement, and theoretical perspectives. Handbook of personality: Theory and research **2** (1999) 102–138
[24] Watson, D., Clark, L.A.: On traits and temperament: general and specific factors of emotional experience and their relation to the five-factor model. Journal of Personality **60**(2) (1992) 441–476
[25] Kesting, A., Treiber, M., Helbing, D.: General Lane-Changing Model MOBIL for Car-Following Models. Transportation Research Record **1999**(1) (January 2007) 86–94