Modelling Personality-Based Individual Differences in the Use of Emotion Regulation Strategies

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Abstract. The modelling of the emotion regulation process is an important aspect that can contribute to the creation of more realistic intelligent virtual agents. The emotional reactions in a virtual agent, produced by the regulation process, can be useful to better adapt the agent's behaviour to the particular requirements of a social interactive scenario. We propose a computational model of emotion regulation where the use of different strategies to down-regulate the negative emotions is based on personality-based individual differences. Our model implements a fuzzy mechanism that reproduce the correlation between different personality traits and the use of the specific emotion regulation strategies described in the literature. The validation of the model has been performed through a set of simulations where synthetic data have been generated to represent individuals with different personalities.

Keywords: Affective computing · Emotion modelling · Virtual agents · Personality traits · Emotion regulation strategies

1 Introduction

The use and benefits of virtual agents, as advanced human-computer interaction interfaces, has contributed to the research and development of better underlying mechanisms able to generate more human-like behaviours in those agents. The modelling of the emotional phenomenon, as a basic component of human behaviour, is a key characteristic to produce *adequate* emotional reactions in the virtual agent while interacting with the user. The generation of emotional reactions that convey *empathy* towards the user is particularly important to create social and emotional bonds that maximise the use of virtual agents. The displaying of specific emotions with a suitable level of intensity is an important aspect especially for applications where the objective of the virtual agent is to support the user with therapeutic-based activities [1].

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The process to modulate the intensity (or even prevent the activation) of a particular emotion is known as emotion regulation. According to [2], there are different strategies that an individual could implement to self-regulate his/her emotions. The implementation of the different strategies for emotion regulation changes across individuals and there are studies that demonstrate the influence of culture, age, gender, temperament and personality traits on the process of emotion regulation [3,4].

Based on the evidence about the correlation between different personality types and the way how individuals self-regulate emotions, we present a computational model of the emotion regulation process considering the individual differences produced by the characteristics of different personalities. Our model is based on J.J. Gross' process model of emotion regulation [2] and integrates the findings about the influence of personality traits (using the Big Five model) in the selection of different strategies for emotion regulation [3,4].

We represent the influence of the personality type on the selection of the emotion regulation strategies through a set of fuzzy logic rules. A set of simulations using stochastic data that represent individuals scoring at different personality type is executed as the input of the fuzzy rules. The implementation or not of each emotion regulation strategy, according to the different personality, is the output of the fuzzy inference system and it is compared with the evidence reported in the literature.

Our main aim is to get a computational emotion regulation component that can be used as the affect derivation and affect intensity models for appraisal-based computational architectures of emotions [5]. The emotions and their associated intensity produced by our proposed model can contribute to generate a richer emotional behaviour in synthetic characters such as embodied conversational agents. Building virtual agents with different personalities able to produce diverse emotional reactions will be useful for the design of better personalised interactive scenarios.

The remainder of the paper is organised as follows: In Sect. 2 the theoretical foundations of the emotion regulation process and a summary of current computational models of this process are presented. The proposed model is described in Sect. 3, and its evaluation is presented in Sect. 4. Finally, Sect. 5 presents the main conclusions and some further work.

2 Related Work

2.1 Theoretical Foundations of Emotion Regulation

One of the affective processes that has attracted the interest of an important number of researchers in the last years is the emotion regulation. Emotion regulation is considered as the *modulation* of a given emotional reaction, including its inhibition, activation or graded modulation [6]. Although there is still discussion about whether consider the emotion regulation process as part of the emotion generation [7,8], there are studies that reveal the neural differences between these two processes [9] and describe the benefits of studying the emotion generation and emotion regulation processes separately [2].

The model of emotion regulation proposed by Gross [2] describes the conscious and unconscious strategies used to increase, maintain, or decrease one or more components of an emotional response. The main characteristic of this model is the identification and definition of five families of emotion regulation processes: *situation selection*, *situation modification*, *attentional deployment*, *cognitive change* and *response modulation*.

Situation selection is described as when an individual takes the necessary actions to be in a situation the individual expects will raise a certain desirable emotion. *Situation modification* refers to the efforts employed by the individual to directly modify the actual situation to alter its emotional impact. The third family, *attentional deployment*, refers to how individuals direct their attention within the current situation in order to influence their emotions. *Cognitive change* is described as when the individual changes how the actual situation is appraised to alter its emotional significance, either by changing how the individual thinks about the situation or the capacity to manage it. Finally, the *response modulation* family refers when the individual influences the physiological, experiential, or behavioural responses to the situation.

Based on experimental work, there is now an agreement about the fact that individuals differ *systematically* and *consistently* in how they apply emotion regulation in every day situations [4]. The Emotion Regulation Questionnaire (ERQ) [10] is an instrument used to identify consistent differences in emotion regulation according to individual characteristics such as age, gender, culture and personality trends. The questionnaire have been validated in different languages and applied to young and older adults from different countries [11–13]. One of the findings from these experimental works is the evidence about the influence of the different personalities on the use of the strategies of emotion regulation [3]. This evidence is the basis of our proposed model explained in Sect. 3.

2.2 Computational Models of Emotion Regulation

The modelling of the emotional phenomenon has produced different computational architectures of emotion that are used to analyse and simulate different aspects of this complex process. Most of these architectures are based on different cognitive and psychological theories of emotions influenced by the components and phases of the emotional phenomenon that the model tries to represent [5]. Although several computational architectures of emotions have been developed in the last years, most of them are dedicated to represent the process of emotion generation and just a few have integrated the process of emotion regulation.

One of the first architectures that modelled the phenomenon of emotion regulation phenomena was EMA [14]. The EMA framework is based on the cognitive appraisal theory of emotions [15] and it integrates a *coping* mechanism with strategies such as *planning*, *acceptance*, *positive reinterpretation*, *mental disengagement*, *denial/wishful thinking* and *shift/accept blame* [16]. The main aim of the coping component in EMA was to better adapt the behaviour of virtual agents to a dynamic environment.

CoMERG is another computational model of emotion regulation based on Gross' theory. This model formalises Gross model through a set of difference equations and rules to simulate the dynamics of Gross' emotion-regulation strategies [17]. CoMERG identifies a set of variables and their dependencies to represent both quantitative aspects (such as levels of emotional response) and qualitative aspects (such as decisions to regulate one's emotion) of the model. These variables include e.g. the level of -the actual- emotion, the optimal -desired- level of emotion, the personal tendency to adjust the emotional value, or the costs of adjusting the emotional value, among others to simulate and evaluate the results in the use of four strategies of emotion regulation. Although the model includes a variable representing a *personal tendency to adjust the emotional value*, the selection of the different strategies of emotion regulation are not based on the characteristics of different personality traits.

The work presented in [18] is an additional model of emotion regulation based on Gross' theory. This model proposes an extension of the CoMERG model by adding a dynamic evaluation of different kind of events and associating levels of desirability of those events, which in turn are used to elicit a set of emotions. The desirability of the events, the impact of the events according to a set of pre-defined goals and the emotional responses are modelled through fuzzy sets. Similar to CoMERG, the model implements an equation to calculate the emotional response. The equation includes different variables to represent the execution of different strategies for emotion regulation. The calculation also contains an *adaptation factor* which indicates the flexibility of the agent toward applying a specific regulation strategy in a certain condition.

A more recent work presents a neurologically inspired computational model of emotion regulation [19]. The model is based on an internal monitoring and decision making about the selection of three (Gross's model based) strategies of emotion regulation: situation modification, cognitive change and response modulation. The decision process to select one or another (or the three) emotion regulation strategies is mainly based on the assessment of the current emotional state generated by an external event, the *sensitivity* of a person for negative stimuli, and the *preferences* of a person for the emotion regulation strategies. The process is modelled as a temporal-causal network using a set of differential equations and evaluated through a number of simulations. During the simulations, different thresholds are set for the intensity of the negative emotions and different weights are defined to represent how much sensitive is the person to the stimulus. The use of these two parameters try to represent the individual differences in the implementation of the emotion regulation strategies.

As can be seen, most of the presented models include variables such as the *preferences*, *tendency* or *flexibility* of a person toward emotion regulation strategies, as well as his/her *sensitivity* for negative stimuli. The setting of these variables in the models where these are implemented try to represent the individual differences during the selection and implementation of the strategies of emotion regulation. Nevertheless, none of the above models associate specific personality traits to the selection of the different emotion regulation strategies. The contribution of the work presented here, is the construction of a computational framework which explicitly implements the individual differences during emotion regulation based on personality. The Big Five personality model and the findings reported in [3] are the theoretical roots of the model described in the next section.

3 The Proposed Model

3.1 Correlation Between Personality and Emotion Regulation Strategies

Most of the existent computational models of emotions based on cognitive appraisal theories implement -implicitly or explicitly- four main components. The **appraisal-derivation** component assesses e.g. how much desirable/undesirable, expected/unexpected and liked/disliked is an event or action occurred in the environment of the agent according to the agent's goals and preferences. The **affect-derivation** component uses the assessment performed in the appraisal-derivation component to generate the specific -positive or negative- emotions according to the type of goals and/or preferences affected by the occurred event or action. A close related component is the **affect-intensity** model which specifies the strength of the emotional response resulting from a specific appraisal. The **affect-consequent** component maps the emotional state produced in the agent into specific behaviours as responses to the detected event/action. For details of these components and their relationship see [5].

Our proposed model of emotion regulation can be seen as the *affect-derivation* and *affect-intensity* components where the produced emotions and their corresponding intensity are obtained after the implementation (or not) of the strategies of emotion regulation. This model is an extension of a previous work where only two emotion regulation strategies were included [20]. In that preceding study, the decision to implement any of the two strategies was based on predefined thresholds for the intensity of negative emotions and some characteristics of the events produced in the interactive scenario where it was evaluated. The selection of the strategies according to individual differences was neglected.

In order to include in our model those individual *preferences* or *tendencies* toward the implementation of specific emotion regulation strategies, we have used the research findings described in [3]. In the referred study, the authors correlate the habitual use of emotion regulation strategies with different personalities using the Big Five personality traits [21]: *conscientiousness*, *extraversion*, *neuroticism*, *openness to experience* and *agreeableness* (see details in [3]). The correlation between the use of the emotion regulation strategies by each personality trait is summarised in Table 1.

A positive correlation between a strategy and a personality trait is represented by "+". For example, individuals *high* in conscientiousness have the ability to plan, organise, and think ahead about potential consequences before

Table 1. Correlation of personality traits to the habitual use of emotion regulation strategies (taken from [3]).

Personality	Situation selection	Situation modification	Attention deployment	Cognitive change	Response modulation
Conscientiousness	+	+	+	0	0
Extraversion	–	+	0	0	–
Neuroticism	(+)	–	–	–	0
Openness	(–)	(+)	+	+	–
Agreeableness	0	–	0	0	(0)

acting. This characteristic should make it easier for them to use *situation selection* strategy. On the other hand, individuals *low* in conscientiousness have more difficulties to avoid entering or getting trapped in situations that cause them negative emotions [3]. A negative correlation is represented by "−". For example, individuals *high* in neuroticism do not usually apply the *situation modification* strategy due to the lack of self-esteem and confidence to assert their needs and enforce specific changes in the situation. When a clear positive or negative correlation has not been found, it is indicated with a "0". The parentheses, such as (+), indicates that the correlation likely depends on other factors or considerations such contextual information of the events, actions or individual's social relationships among others.

3.2 Fuzzy Sets and Fuzzy Rules

The linguistic values representing the *degree* of the different personality traits in an individual, such as *low in conscientiousness* or *high in extraversion*, are obtained from standardised inventories which score each of the Big Five traits. Moreover, the events or actions produced in the individual's environment can be appraised as *bad*, *neutral* or *good* according to the goals of the individual and predispose the triggering of an emotional response. Based on these linguistic values, we decided to use fuzzy sets to express these values in the main variables of our model. Fuzzy rules are used to represent the correlation between the different degrees of personality traits and the five strategies of emotion regulation.

The sets and elements used in our model are the following:

$P \in PERSONALITY = \{Co, Ex, Ne, Op, Ag\}$ is a *personality trait* element,
$E_i \in EVENT = \{E_1, ...E_m\}$ is an occurred *event* element, and
$S \in STRATEGY = \{SitSel, SitMod, AttDep, CogChg, ResMod\}$ is an *emotion regulation strategy* element.

The valuation function on each set is as follows:

$p : PERSONALITY \rightarrow V_p = \{low, middle, high\}$. (1)
$e : EVENT \rightarrow V_e\{very\_bad, bad, neutral, good, very\_good\}$. (2)
$s : STRATEGY \rightarrow V_s = \{weak\_apply, mid\_apply, strong\_apply\}$. (3)

The set $PERSONALITY$ contains the five personality traits and the distribution of linguistic values (V_p) of the personality traits implemented through fuzzy sets using a Gaussian membership function. The boundaries of each fuzzy set are based on the values used in the Big Five questionnaire. Similarly, the set $STRATEGY$ contains the five strategies of emotion regulation and the linguistic values (V_s) indicates to what extent each strategy is applied. Finally, the *events* occurred in the environment of the agent are linguistic qualified by values in V_e, which are also implemented through fuzzy sets with a Gaussian membership function. The fuzzy sets are shown in Fig. 1.

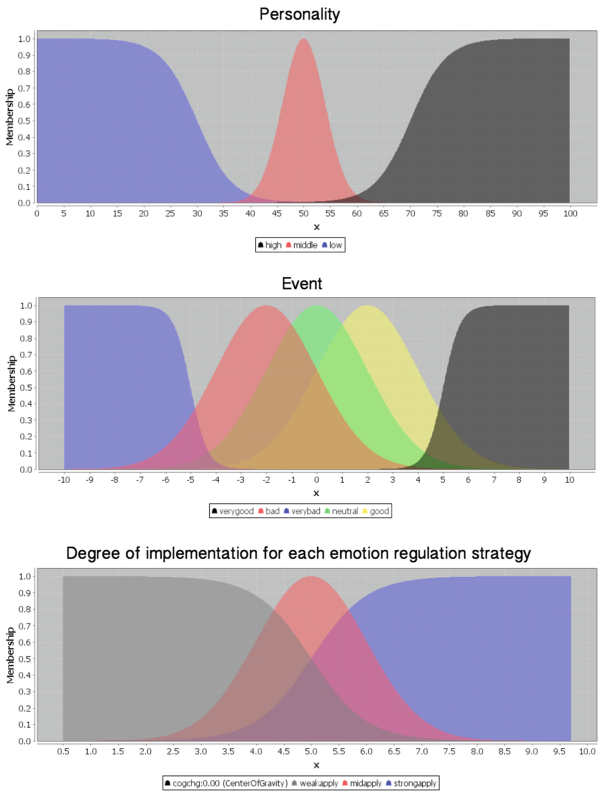

Fig. 1. Fuzzy sets used in the model.

The correlation between the personality traits and to what extent what of the five strategies of emotion regulation an agent will apply is implemented through a set of fuzzy rules. A roughly formal account of the rules is:

event AND personality THEN strategy

Then we have rules instances of the type:

$IF(E_1\ IS\ bad\ OR\ E_1\ IS\ very\_bad)\ AND\ (Co\ IS\ high)$
$THEN\ SitSel\ IS\ strong\_apply$

$IF(E_1\ IS\ bad\ OR\ E_1\ IS\ very\_bad)\ AND\ (Ex\ IS\ middle)$
$THEN\ ResMod\ IS\ mid\_apply$

$IF(E_1\ IS\ bad\ OR\ E_1\ IS\ very\_bad)\ AND\ (Ag\ IS\ low)$
$THEN\ SitMod\ IS\ weak\_apply$
...

As explained above, the antecedents and consequents of the fuzzy rules are based on the evidence summarised in the Table 1 with the following considerations:

1. The cases where there is no a clear evidence between the personality trait and the selection of a specific emotion regulation strategy (those cases labeled with "0" in Table 1), the consequents of the rules involving those personality traits are set to *mid_apply*. As the final value of the strategy to apply is a combination of all the fuzzy rules with all the personality traits, the implementation or not of each specific emotion regulation strategy will be influenced by the values in the rest of the personality traits.
2. The cases where some contextual information of the event or social relationships of the agent are required to decide the implementation or not of specific emotion regulation strategies (those cases shown in parentheses in Table 1), the consequents of the rules were set with the value specified in the Table 1. Nevertheless, when this proposed model is integrated into a computational architecture of emotions, these cases will be complemented by the contextual information of the events triggered during an interactive scenario. In this sense the previous work reported in [20], where only the information generated during the interaction was used to decide whether to apply the emotion regulation process, will be enriched with the model described here.
3. As most of the research on emotion regulation has been concentrated on negative emotions (produced by the negative events or actions in the agent's world), the current set of fuzzy rules only uses the values *bad* and *very_bad* of the events as part of their antecedents. Nevertheless, the model can be easily extended to up-regulate positive emotions using the values *good* and *very_good* of an event.

4 Evaluation

The model was implemented as a java software module using the jFuzzyLogic library [22]. In order to validate that the results provided by the fuzzy inference system are in line with the correlations shown in Table 1, a set of simulations was run. At each simulation step, random values were generated for each of the five personality traits. These values simulated the obtained score by a person from the Big-Five personality inventory and were fuzzified using the fuzzy sets described in Sect. 3.2. Moreover, random values were also generated to represent the appraisal of an hypothetical event, and also fuzzified. Both, the fuzzified values of each personality trait and of the event, were used as the input for the fuzzy inference system. A total of 5,000 simulation, representing the same number of individuals, were executed.

The result provided by the inference system was the *degree of use* of each emotion regulation strategy labeled as *weak_apply*, *mid_apply*, and *strong_apply*. In order to quantify the result obtained in each of the five strategies of emotion regulation, we applied the Mamdani [23] model by using the centroid defuzzification of the fuzzy rules. The obtained crisp values of the 5,000 simulations were plotted in a scatter graph to visualise how the different emotion regulation strategies are applied by each of the five personality traits. An example is the plot of Fig. 2 that presents how the *situation selection* and *situation modification* strategies are used by the *extraversion* personality trait.

Fig. 2. Use of *situation selection* and *situation modification* strategies in the *extraversion* personality trait.

According to the summary of Table 1, individuals high in extraversion are negatively related with the use of situation selection and positively related with the use of situation modification. This assumption is reflected in the graph where lower values for this personality trait generate high crisp values in the use of situation selection. The use of the situation selection strategy decreases when the score in extraversion increases. Exactly the opposite occurs with the use of the situation modification strategy: low values in extraversion generate low crisp values for the use of this strategy, and it increases when scores of extraversion are also increased.

The plot of Fig. 3 shows the obtained results for the neuroticism personality trait. The values related to high scores of neuroticism are negatively related with the use of *situation modification*, *attentional deployment* and *cognitive change*. The only strategy that is positively related with high neuroticism is the *situation selection*. These results clearly reflect the correlations presented in the Table 1 for this personality trait.

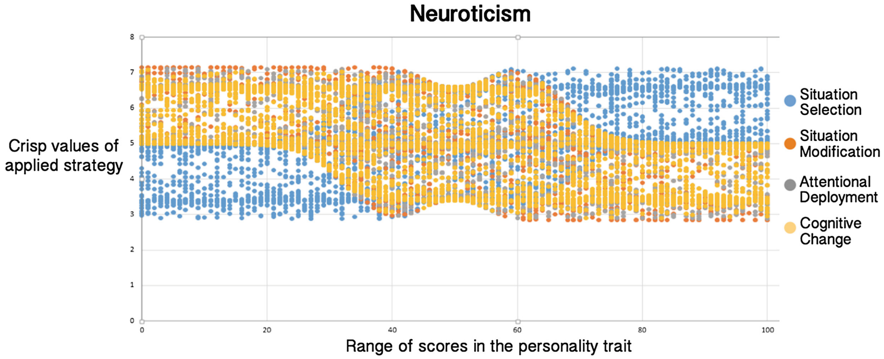

Fig. 3. Use of four strategies of emotion regulation in the *neuroticism* personality trait.

The cases where there is no a clear evidence of the correlation between the type of personality and the habitual use of specific emotion regulation strategies (those labeled with "0" in Table 1) are also reflected in the results obtained from the simulations. An example of these cases is for the *agreeableness* personality trait reflected in Fig. 4. The crisp values of three emotion regulation strategies remain in a same range independently of the personality's score.

Similar results are obtained for the other two personality traits: *openness* and *conscientiousness*. After the generation of 5,000 simulated data, the crisp values of the different applied strategies reflect the correlation shown in Table 1 but for the restrictions of space, the corresponding plots are not presented here.

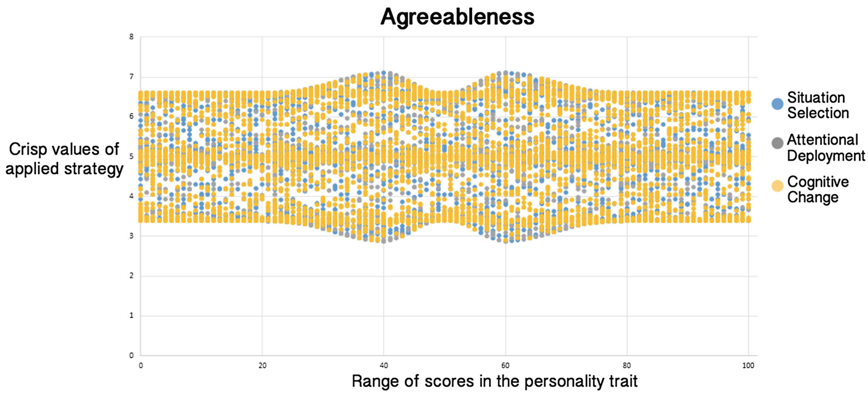

Fig. 4. Results of *situation selection*, *attentional deployment* and *cognitive change* in the *agreeableness* personality trait.

5 Conclusions

This paper presents a computational model of emotion regulation based on existing evidence about the personality-based individual differences in the use of different strategies to down-regulate negative emotions. The proposed model implements, using a fuzzy logic inference mechanism, the correlation between the different -Big Five- personality traits and the five strategies of emotion regulation proposed by J.J. Gross. The main aim of the proposed model is to be integrated as the underlying mechanism for the affect-derivation and affect-intensity components in a computational architecture of emotions. The generation of different emotion's intensities (generated by the emotion regulation process) based on different personalities will contribute to the creation of more believable virtual agents that can be personalised to the specific requirements of interactive scenarios.

The next step is exactly the integration of the model presented here into an existent computational architecture of emotions and complement the work initiated in [20]. In this way, the validation presented in this paper based on a set of simulations, can be complemented through the evaluation of the emotional behaviour produced by different virtual agents in a specific interactive scenario. The crisp values obtained from our fuzzy inference system can be used in a function to down-regulate the intensity of a triggered -negative- emotion. Thus, the produced emotional reactions modelling different personalities can be compared with those produced in virtual agents that do not incorporate our model and compare the acceptability and preferences of the users.

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