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Designing Emotions

An Empirical Approach to Realistic Affect Simulation

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Abstract While current virtual characters may look photorealistic they often lack behavioral complexity. Emotion may be the key ingredient to create behavioral variety, social adaptivity and thus believability. While various models of emotion have been suggested, the concrete parametrization must often be designed by the implementer. We propose to enhance an implemented affect simulator called ALMA (A Layered Model of Affect) by learning the parametrization of the underlying OCC model through user studies. Users are asked to rate emotional intensity in a variety of described situations. We then use regression analysis to recreate these reactions in the OCC model. We present a tool called EMIMOTO (EMotion Intensity MOdeling TOol) in conjunction with the ALMA simulation tool. Our approach is a first step toward empirically parametrized emotion models that try to reflect user expectations.

Keywords Affective Computing · Emotion Simulation · Embodied Conversational Characters

1 Introduction

Affective computing [19] usually refers to the recognition of emotion to adapt the interaction to a user's current state of mind, to create empathy. However, the expression of emotion has equally received attention, in particular in the area of intelligent virtual agents [23] where current research is trying to abstract from animation problems to higher levels of behavior [10], intention [7] and social relations [20]. This is accompanied by a general interest of the computing sciences to join forces with psychologists and social scientists on this topic, as evident in networks of excellence like HUMAINE[1] or SSPNET[2], and the W3C standardization effort of EmotionML[3] that aims at being an interface between the three areas of manual data *annotation*, emotion *recognition* and emotional *behavior generation* (including face/body animation).

In the area of behavior generation it has been shown that emotion is not only expressed with the face but also with the rest of the body, from posture to gesture [24]. Even a simple feature like the handedness of a gesture may be correlated with a person's emotional state [11]. Expressing emotion via the face, the arms and hands or the whole body is essential in overcoming what many people refer to as the *uncanny valley*, a term going back to Mori [17]: Mori hypothesized that when surface realism reaches almost human-likeness, people are taken aback. One reason may be that the behavioral realism cannot keep up with the surface, thus creating a gap that leads to a "zombie-like" discrepancy between perfect surface and robotic motion. No matter whether this hypothesis is true, in the world of computer games, a strong sense of autonomy of non-player characters is certainly desirable. On a more fundamental level, emotions affect the agent's decision making and deliberation processes [16]. Therefore, emotion simulation can be used in computer games to trigger "irrational" decisions, made e.g. in a state of stress, excitement or hatred. Emotions thus have the potential to increase the believability of agents on various levels.

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[1] http://emotion-research.net
[2] http://sspnet.eu/
[3] http://www.w3.org/TR/emotionml/

Another area of interest are embodied agents as companions and assistants, e.g. for people with special needs [1]. Because of their embodiment they could be used to synthesize sign language, providing communication services for the deaf [9]. Deaf people often have difficulty reading text since it is not their native language. An automatic signing avatar would greatly facilitate access to websites and other written content. However, while research has mainly focused on controlling the hands, a recurring criticism from deaf test users is the missing emotionality of signing avatars [8]. In fact, recent studies (not published yet) in our group indicate that emotional expression may contribute to comprehension for the simple reason that it allows deaf "listeners" to focus on the (emotional) face. When the face is expressionless the onlookers gaze wanders back and forth between face and hands which is unusual in a human context (where people always fixate the face) and therefore, avatars are harder to understand.

In order to endow virtual characters with synthetic emotion, implemented models of affect are needed that are capable of mapping outside events to changes in the internal emotion model. Ultimately, the emotional state can be synthesized using high-level languages like BML (behavior markup language) [6,12,22]. In this article we describe two tools that allow the psychologically informed modeling of emotion state and the empirical fine-tuning necessary to any such model.

The article is organized as follows. We first review existing computational emotion models (Sec. 2) before giving an overview of ALMA (A Layered Model of Affect) in Sec. 3. We motivate the problem of finding intensity functions in Sec. 4 before explaining our empirical data collection (Sec. 5) and modeling approach (Sec. 6) in detail. We conclude with a summary and future work.

2 Related Work

In the field of embodied agents, only a few of the existing emotion theories have been subjected to operationalization. Gratch et al. give a comprehensive overview of widely used models and their relationship [5]. One of the most popular theories is the *cognitive model of emotions*, also called OCC, named after their three authors [18]. While our own work is based on this model, we want to quickly review two related models: the AR model and PEACTIDM. In all models the decisive process under investigation is *appraisal*, i.e. the emotion state changes depending on how a situation is appraised (beneficial, likely, controllable ...).

The *affective reasoner model* (AR) is based on the OCC model but refines it to allow reasoning from a third-person perspective [2]. An expert system using AR is able to find out why a person is upset/angry based on the circumstances and thus, to distinguish when to give rational advice and when to show empathy. To make this possible a number of intensity-modulating variables are introduced, some of which are derived from the OCC model (goal realization, blameworthiness ...) while others are novel (certainty, emotional interrelatedness, valence bias...). However, while the general framework is an important refinement of OCC, the question of how to compute intensities of emotions is not resolved and left to the intuition of the implementer.

The PEACTIDM model [13] is based on ideas by Scherer [21]. It defines nine influencing variables and spells out an equation to compute the final emotion intensity. The variables are: suddenness, goal relevance, intrinsic pleasantness, conductiveness, control, power, unpredictability, discrepancy from expectation and outcome probability. While the overall computation appears to be plausible it is unclear how well concrete values are realistic.

The only empirical approach to the intensity problem that we are aware of was conducted by Gratch et al. [5] who grouped the existing approaches into categories: expected utility model, expectation change model, threshold model, additive model, hybrid model. According to their reasoning the two central variables are that of probability and utility. For every category they devised the respective formula and then, conducted an empiricial study to see which function would best fit the data. While their results are a first step toward an empirical parametrization of emotion models, the selection of the two variables somewhat restricts the direct utility of the data. We build on Gratch et al. but include a wider set of variables and choose a different data collection scenario.

3 An Overview of ALMA

For the simulation of emotions, we rely on ALMA [3, 4] (A Layered Model of Affect) which is both a model and a software. It combines the OCC cognitive model of emotions developed [18], the "Big Five" model of personality [14] and a simulation of mood based on the Mehrabian's notion of PAD (pleasure, arousal, dominance) space [15]. The relations between these different types of affect are a central part of the affect simulation, depicted in Fig. 1: A given *personality* defines a default mood and influences the intensities of different emotions. The current *mood* amplifies or dampens the intensities of emotions. *Emotions* as short term affective events influence the longer-term mood.

Elicited emotions influence an individual's mood. The higher the intensity of an emotion is, the greater the particular mood changes. Emotions usually do not last forever. Over a specific period the intensity of emotions decays and the influence on the current mood fades.

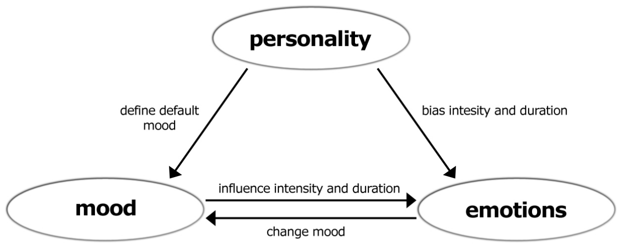

Fig. 1 Simulated relations between different affect types.

This computational model of emotions provides several methods for a situational appraisal, which is usually the first stage in a cognitive inspired simulation of emotions:

– *Emotion Eliciting Conditions (EECs)*. Based on the theory of emotions from Ortony, Clore, and Collins [18] EECs represent an appraisal of an situation that includes events of concern to an individual, actions of those s/he consider responsible for such actions, and objects/persons. EECs are the basic input type for the emotion simulation. Example: the ECC *(praiseworthiness* $= 0.8 \cdot$ *praiseworthy, agency* $=$ *self)* stands for the appraisal of a situation in which the agents own (agency = self) action has been appraised as highly (0.8) praiseworthy.
– *Basic appraisal rules* simplify the appraisal of events, actions, and objects. For example, an event like "the sun is shining" is appraised as GoodEvent. Technically, they serve as symbolic abbreviations for EECs.
– *Dialog Act appraisal rules*. They define how an agent appraises its own acts and other agents acts. Dialog acts specify the underlying communicative intent of an utterance, e.g. tease, or congratulate. For other characters acts the performing character had to be specified. In this case, we differentiate between being directly addressed (direct) and being in the position of a listener (indirect). From a technical point of view, these rules are symbolic abbreviations for basic appraisal rules and EECs.

ALMA combines an appraisal mechanism with a dimensional representation of emotions which can be used to model the emotions' development over time. Overall, three affect types are simulated, as they occur in

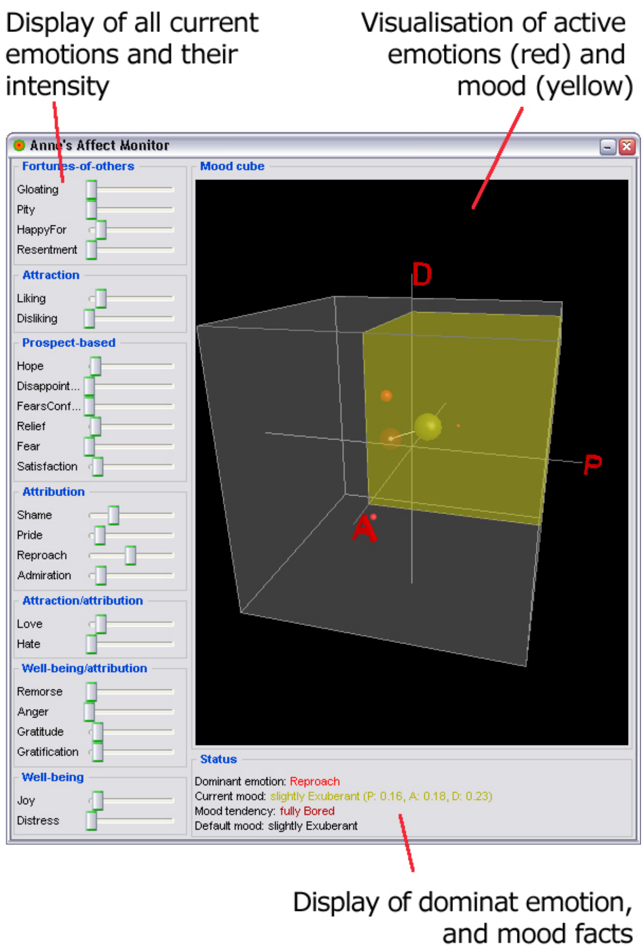

Fig. 2 The ALMA affect monitor.

human beings: (1) emotions (24 types, see Fig. 2, left side) reflect short- term affect that decays after a short period of time; (2) moods (8 types, see Fig. 2, right side) reflect medium-term affect, which is generally not related to a concrete event, action or object; and (3) personality (5 traits) reflects individual differences in mental characteristics and affective dispositions.

In the following we focus on the first type of affect, emotions, and answer the question how to identify good functions for computing the intensity of the basic emotions, given some input EECs.

4 Informing the OCC Component of ALMA

While ALMA allows to modulate the intensity of emotions using different affect types that model different time scales (short/medium/long-term), a simpler question remains unsolved: how to define the initial mapping from emotion eliciting conditions (e.g. a desirable event like winning the lottery or a blameworthy action like being betrayed) and the intensity of the output emotion (e.g. joy or reproach)? While Gratch et al. approached this question by identifying common principles shared by different models and reducing them to two variables [5], we focus on a single model, the OCC model, and try to include various variables. In OCC, the central variables are desirability, praiseworthiness and appealingness. While we ignore the so-called global variables (sense of reality, proximity...), we include most of the so-called *local variables* (e.g. likelihood, effort, realization ...).

Thus, for every emotion category (fear, joy, hope, ...) we define a number of input variables (e.g. desirability, likelihood etc.) to a function that models the emotion's intensity as a value between 0 and 1. The main idea of our study is to let human users estimate both input and output value, based on a described situation. In the analysis, we fit a multivariate function to the given data and plug this function into the appraisal component of the ALMA tool. An example of how an emotion intensity may be calculated is `fear` which is a function of the variables `desirability` (D $\in [-1, 0]$) and `likelihood` (L $\in [0, 1]$). The less desirable an event is, the more fear is generated. The higher the likelihood that the event will occur, the higher the fear. The intensity I_{fear} could be modeled as $I_{fear} = -0.7 \times D + 0.3 \times L$. But it is not clear whether these parameters are correct nor whether a linear combination is a good choice at all. In ALMA, functions like these are needed for the first layer of affect, also called appraisal (Sec. 3)

5 Empirical Data Collection

For the data collection we used pen-and-paper questionnaires. Subjects are instructed to imagine a number of situations of emotional content in a computer games context. Future versions of this study will utilize real gaming situations or virtual reality surroundings, to actually immerse the user in a situation that closely resembles the one described in the questionnaire. For our domain we decided to use computer games because such games are widely known and put players in situations where basic emotions like fear, hope, joy etc. are likely to occur, both in the player and in the non-player characters. Another reason for this domain is that it is a likely candidate for the actual application of this type of research.

We chose an ego shooter game scenario and formulated descriptions of short episodes. These descriptions sometimes even related to each other to allow us to arrive at more complex situations without overburdening the user with too much description. An example scenario is the following:

Scenario Imagine you are playing an ego shooter game where your team is competing against another team. The team with the last surviving member wins.

Conditions You deem the other team stronger. How do you estimate the following parameters:
- How much would you like to win? (Desirability: -5 to +5)
- What are your chances of winning? (Likelihood: 1 to 10)

Resulting emotion How strongly would you experience the following emotions:
- Hope (1 to 10)
- Fear (1 to 10)

In total, 17 subjects participated in the study (all male, ages 15–30, average 23 years). All subjects had some familiarity with computer games, on average 8 (on a scale of 1 to 10). Participants did not have a time limit and were not paid. The 17 questionnaires resulted in 2924 data points.

Using the collected data, we conducted a regression analysis. We presupposed two constraints for the selection of potential functions. First, the function must not leave the target interval of $[0, 1]$ for intensity. Every function can be made to adhere to this criterium by *clamping*, i.e. mapping values outside this interval to the closest boundary point (0 or 1). Second, every function must have a *monotonic* increase .This reflects the fact that e.g. a more desirable event cannot result in less intense joy, given that all other circumstances are the same. The analysis process will be described in the next section.

6 Modeling in EMIMOTO

For a detailed analysis we created the Emotion Intensity Modeling Tool (EMIMOTO) that graphically depicts regression curves based on the various user choices (function type, parameters ...). Fig. 3 shows a screenshot with fitted curves for the emotion *resentment*. The tool expects user rating data in a simple table format and then offers to test various regression functions which are evaluated using the correlation coefficient R^2.

6.1 Regression Analysis

Our analysis is built on univariate regression analysis where we offer the following functions: linear, exponential, logarithmic, geometric, polynomial (degrees 2, 3 and 4). This analysis can only be applied to the few emotions with a single input variable (Hope, Joy, Distress).

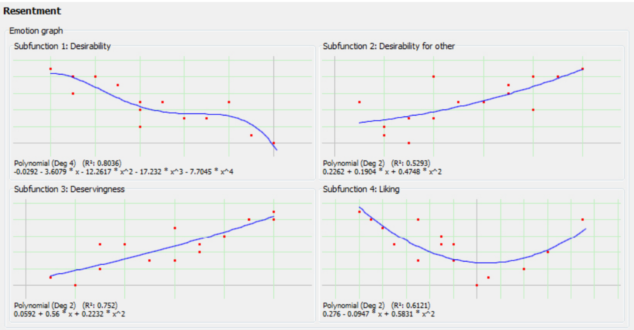

Fig. 3 Our analysis tool allows an intuitive navigation through modeling choices.

For all other emotions we resort to multivariate regression. We distinguish two types of multivariate regression. The first is a simple linear multivariate regression over all input variables. The second variant uses, for n input variables, n separate univariate analyses to compute the optimal functions f_i ($i \in \{0, ..., n-1\}$), which are in turn run through the linear multivariate analysis that attaches weights to the functions: $a_0 + a_1 * f_1 + ... + a_{n-1} * f_{n-1}$.

Table 1 shows the resulting best functions for those emotions where R^2 arrived at a reasonable level ($> .2$), where we use the following variables: desirability (Des), praiseworthiness (Prs), liking (Lkg), desirability for others (DfO), deservingness (Dsv), expectation deviation (ExD), hope (Hope), effort (Eff), strength of unit (StoU) and fear (does not occur in the listed emotions).

Emotion	Intensity function	R^2
Gloating	1.13 + .87 Des − .68 DfO + .94 Dsv − 1.86 Lkg	0.60
Anger	0.16 − 0.33 Prs − 0.57 ExD − 0.59 Des	0.53
Gratitude	0.17 + 0.37 Prs + 0.12 ExD + 0.32 Des	0.49
Admiration	−6.62 + 0.90 Prs + 10.15 ExD	0.44
Hope	0.37 + 0.98 Des − 1.87 Des^2 + 1.36 Des^3	0.42
Disappointment	−0.38 + 0.82 Hope + 0.76 Eff	0.36
Gratification	0.32 + 0.08 Prs + 0.09 StoU − 0.11 ExD + 0.42 Des	0.32
Happy-for	.61 + .07 DfO − .03 Dsv + .22 Lkg	0.29
Pride	0.69 + 0.24 Prs + 0.06 StoU − 0.31 ExD	0.24
Reproach	−0.15 + 0.96 Prs + 0.60 ExD	0.22
Shame	−0.34 − 0.10 Prs + 1.14 StoU + 0.79 ExD	0.21
Satisfaction	−0.65 + 0.91 Hope + 0.96 Eff	0.21
Joy	0.44 + 1.38 Des − 2.53 Des^2 + 1.55 Des^3	0.21

Table 1 Best intensity functions for a selection of emotions. The following emotions had scores below 0.2: Relief, Resentment, Remorse, Fears-confirmed, Fear, Distress, Pity.

6.2 Application and Testing

For simple testing we use a lightweight OCC implementation in the rule based system JESS[4] (Java Expert Systems Shell) which is loosely based on the well-known CLIPS expert system shell. EMIMOTO pastes in the best function for each emotion as JESS code and runs a test set of emotion eliciting conditions to show the user what intensities result. The code snippet in Fig. 4 illustrates how OCC is implemented in JESS: the input is represented with emotion eliciting conditions (EECs) that contain e.g. the *desirability* of an event as a value between -1 and 1. A typical processing rule like *hope* is fired if an EEC fulfills certain preconditions (e.g. for hope it must be a future event) and then applies an intensity function, here called *hope-function*. This is the function that EMIMOTO provides based on the regression analysis.

In a result window the system shows the user the results of various test cases. On a split screen (Fig. 5) a set of simple standard functions are used for intensity computation, on the opposing side the computed functions are used. With this tool, the emotion designer can check whether the computed functions make sense on a selected set of situations.

[4] http://www.jessrules.com/

7 Conclusion

Affective interfaces and games require the realistic simulation of emotion. Prior work on emotion simulation is usually derived from the psychological literature and therefore, the operationalization is not straightforward and involves many design decision.

We presented one such model, ALMA, which is also a software tool and allows to model the interplay between three layers of affect: emotion, mood and personality. In order to make the *design process* involved in any such model more plausible, we attempted to empirically derive part of the simulation parameters from user ratings. These parameters were the intensity func-

```
(deftemplate eec
   "Emotion-eliciting condition"
   (slot id)
   )

(deftemplate event extends eec
   "Emotion-eliciting event"
   (slot desire (type FLOAT))
   )

(deftemplate prospect-based extends event
   "Prospect-based event"
   (slot has-occured (type ATOM) (default no))
   (slot is-future (type ATOM) (default yes))
   (slot likelihood (type FLOAT))
   )

(defrule hope
   "Something may happen that I really want to occur."
   (prospect-based
  (id ?id)
  (desire ?des&:(> ?des 0))
      (is-future ?f&:(eq ?f yes))
      (has-occured ?ho&:(eq ?ho no)))
   =>
   (assert (emotion (type HOPE)
         (intense (hope-function ?des))
         (cause ?id))))
```

Fig. 4 In our lightweight JESS implementation of OCC our EMIMOTO tool replaces intensity functions like *hope-function* with the empirically derived function.

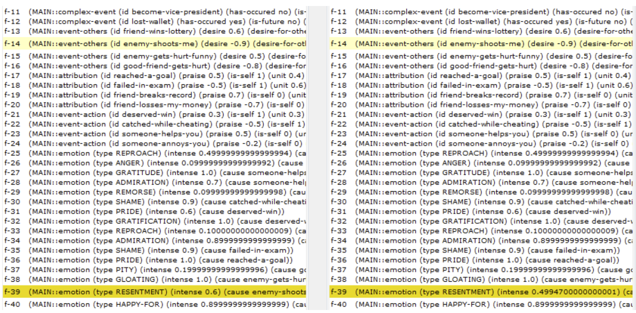

Fig. 5 On a split screen, the user can compare the results of an emotion simulation with standard functions (left) to the results achieved with the empirically derived functions (right).

tions of the OCC emotions (e.g. the intensity of fear as a function of the degree of desirability and likelihood of an event). We suggested to use user ratings and regression analysis to derive these functions and plug them into the overall ALMA framework.

User rating only reflect a subjective view on emotions. This is appropriate for the application in computer games where gamers would see non-player characters behave according to models based on user expectations. However, if a more "realistic" simulation is desired, the use of biometric sensors (skin conductance, heart rate etc.) becomes a necessity.

A systematic evaluation of our methodology remains to be done: does our model really meet the expectations of the users in practice and is the enhancement significant when compared to simpler functions? The present study is a first step with a modest number of subjects and a simple pen-and-paper questionnaire. For the future we plan to create immersive setups for the data collection and a focus on those emotions that are most promising for modeling in this framework.

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