Modelling of Emotional Development within Human-Computer-Interaction

Ingo Siegert * **Kim Hartmann** * **Stefan Glüge** *
Andreas Wendemuth *

* *Cognitive Systems Group, Otto von Guericke University Magdeburg, Universitätsplatz 2, 39106 Magdeburg, Germany*

Abstract: Future trends point towards the usage of technical systems as companions, adaptable to the user's individual skills, preferences and current emotional state. To enable technical systems to determine a user's emotion, current research focuses on emotion recognition. Besides emotions, personality and moods are eminent as well. Standard emotion recognizers do not consider them adequately and therefore neglect a crucial part of user modelling. The challenge is to gather reliable predictions about the observed emotion of the user and, beyond that, recognise changes in the users emotional reaction during interaction.
In this paper we present a mood model that incorporates personality traits based on emotionally labeled data.

Keywords: Emotion, Mood modelling

1. INTRODUCTION

Future trends point towards the usage of technical systems as companions, adaptable to the user's individual skills, preferences and current emotional state (cf. Wendemuth and Biundo [2012]). To enable technical systems to determine a user's emotion, current research focuses on emotion recognition. Today, the community is able to recognize emotional episodes from speech, mimics, and bio-signals with reliable confidence, cf. Batliner et al. [2011], Busso et al. [2004], Walter et al. [2011]. This enables us to build emotion-aware computers, that recognize emotions and react with rule-based dialogue strategies.

Becker [2001] stated that emotions play a major role in human cognitive functions, however the exact correlation is still being discussed. Picard [2000] pointed out that rule-based solutions are not sufficient to understand and predict human behaviour and intelligence. Beside observations and/or expert given rules, a description of the inner mental state of the user is necessary. Hence, to develop truly “affective computers” further research must be done.

A first approach towards modelling the inner mental state by an appraisal-based model and an according framework for the user emotion determination has been presented in Hartmann et al. [2012] and Kotzyba et al. [2012].

However, for a companion technology it is not only necessary to understand the user's current emotional reaction, but to understand the future effects of the user's reaction on the Human-Computer-Interaction (HCI). Without understanding the effects the user's current behaviour and emotional reactions have on the HCI, a cognitive system can not interact future-oriented as a companion.

A central aim of affective computing is the prevention of negative HCI. To enable a system to prevent negative interactions, this type of interaction must be recognised and countermeasures must be taken. Negative interactions may be identified according to the user's emotional development, hence sufficient countermeasures should be chosen on this basis.

A first step towards the recognition of negative interactions is the recognition of the user's emotional state and the prediction of the effects the current state has on the HCI. In André et al. [2000] and Kopp et al. [2005] approaches are presented that allow virtual characters to react in an emotionally natural way.

To predict the effects of a user's emotional state on the ongoing HCI, the modelling of the user's mood is necessary. The user's mood is subject to the user's emotional development and therefore allows to predict the continous developmnt of the interaction. The presented technique allows us to incorporate the temporal emotional development in our mood model and herewith enables us to predict and identify changes in the emotional trend.

In this paper we present a modelling technique that is able to define and predict a user's mood course during system interaction, based on emotional assessments. Furthermore, we suggest a procedure to integrate personality traits in our mood model. We will evaluate the proposed implementation on labelled data from two different non-acted audio-visual databases.

The remainder of this paper is structured as follows: The next section 2 introduces the underlying theories and research results needed to introduce our mood model. Section 3 presents the methods used and the details of the presented mood model. Furthermore, mood transitions are introduced and the integration of personality traits are explained.

Section 4 describes the experimental set-up and presents the results of our experiments. Furthermore, the presented mood model is evaluated. Subsequently, in section 5 we briefly conclude our ideas and discuss potential improvements. An outlook on our ongoing and future research activities is given.

2. BACKGROUND OF THE WORK

In the following section we will give a short excursion into the history of emotional psychology research. The aim of this section is to introduce standard and common notations for emotions and mood and to explain how these are related. Furthermore the correlation between emotion, mood and personality is discussed.

2.1 Categorical and dimensional emotion theories

Emotions can be illustrated either through categories or through dimensions. McDougall [1919/2001] introduced the concept of basic emotions as psychologically primitive building blocks. Functional behaviour patterns are named with descriptive labels, such as “anger” or “fear”. Ekman [2005] extended this model by exploring emotions that are expressable and recognisable through similar facial expressions in many cultures.

Another extension was made by Plutchik [1980], who described the emotional categories in a three-dimensional space. This allowed a structured representation of emotions (see Fig. 1) and made it possible to infer the effects of bipolarity, similarity and intensity. It is still an open debate which emotions should be regarded as single categories and which are components of “emotion families”. Furthermore, the choice of relevant emotion categories for HCI and their specific significance to HCI are still being investigated.

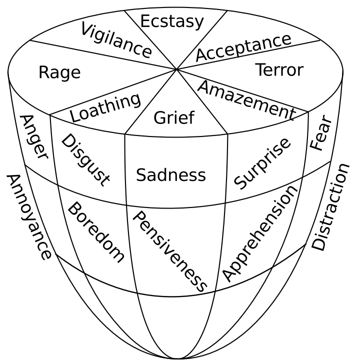


Fig. 1. Plutchik’s three dimensional structural model of emotions (after Plutchik [1980], p. 157).

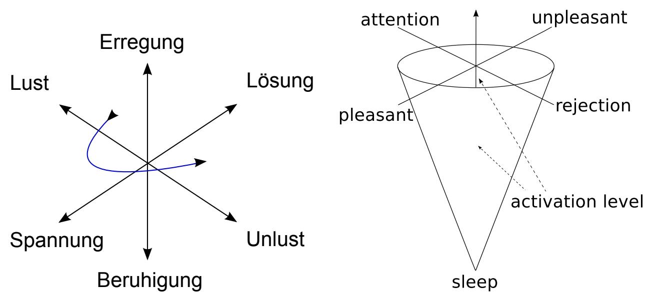
Wundt, who found the distinction into basic and non basic emotions misleading and introduced a so-called “total-feeling” Wundt [1922/1863]. The idea is to represent a “feeling” as a mixture of potentially elementary feelings, each described as a single point in a three dimensional emotion space (pleasure ↔, excitement ↔ inhibition, tension ↔ relaxation), see Fig. 2(a). According to Wundt, an external event triggers a sequence of total-feelings over time, resulting in a specific, continuous course within this three dimensional space. The specific course within the three dimensional space is described by a trajectory through the emotional space. An advantage of this approach is that emotions may be described independently of categories and emotional transitions are an inherent part of the model. Unfortunately, Wundts theory does neither locate single emotions in the emotional space, nor does it provide a solution for the integration of intensity levels.

The exact configuration and dimension of the emotional space has been discussed widely within the research community. Prominent results are those of Schlosberg, Plutchik and Russel.

Schlosberg [1954] examined an activation axis (comparable to excitement ↔ inhibition) on the basis of emotional picture ratings. He used the dimensions pleasantness ↔ unpleasantness, attention ↔ rejection and “level of activation”. Schlosbergs activation dimension may be identified as similar to Plutchiks intensity dimension (see Fig. 2(b)).

Russel [1980] argued against the necessity of a third dimension. His circumplex model of core affect consists of two dimensions: Pleasant ↔ unpleasant and activation ↔ deactivation. Russel proved that - in many cases - the two dimensions attention-rejection and activation (as used in Schlosberg [1954]) are statistically indistinguishable.

Despite the discussions regarding the need of a third dimension, most researchers identified two dimensions needed for the description of emotions: pleasure and arousal. The question for the need of a third dimension



(a) Wundt’s three axes of an orthogonal emotion space, with emotion trajectory (after Wundt [1922/1863]).

(b) Schlosberg’s conic emotion diagram (after Schlosberg [1954], p. 87).

Fig. 2. Representations of dimensional emotion theories.

is subject of ongoing discussions. Relevant results for our research are the investigations of Russel and Mehrabian [1974], who examined the differences between “anger” and “anxiety” and argued pro a third dimension called “dominance”. Through further investigations, Mehrabian and Russell [1977] were able to emphasize that three dimensions are needed to distinguish emotional states. Furthermore, Mehrabian and Russell [1977] also presented the localization of 151 emotional terms in the “pleasure-arousal-dominance-space” (pad-space).

A major criticism of the findings of Russel and Mehrabian is the question of reliability. In a comprehensive study by Gehm and Scherer [1988], using German emotion describing words, the findings of Russel and Mehrabian could not be replicated. However, an explanation of the “irreproducibility” may be that the ability of subjects to rate the emotionally relevant adjectives or pictures was not taken into account (cf. Scherer et al. [2006]). This may also lead to different dimension labels.

Tab. 1. Selected emotion categories in terms of pleasure, arousal and dominance.

Emotion	p	a	d
Anger	-0.51	0.59	0.25
Disappointment	-0.30	-0.40	-0.40
Gratification	0.6	-0.3	0.4
Joy	0.4	0.2	0.1
Satisfaction	0.3	-0.2	0.4

For our purpose, the categorical emotion theories have the advantage of common terms, whereas the dimensional theories inherently incorporate emotional transitions. For a mood model the use of a combination of both theories seems necessary.

In the following sections we use the dimensions pleasure, arousal, and dominance, which are generally accepted as independent. However, we are aware that some investigations show, that the variance of dominance is quite small.

The used emotional space has the three traits pleasure (p), arousal (a) and dominance (d). The implementation of this space uses values from -1.0 to 1.0 for each dimension. They can be described with the following assignment: +p and -p for pleasant and unpleasant, +a and -a for aroused and unaroused, and +d and -d for dominant and submissive.

2.2 Correlation of emotions, mood and personality traits

Emotions reflect short-term affects, usually bound to a specific event, action, or object, cf. Becker [2001]. Hence, an observed emotion reflects a distinct user assessment, that is related to a specific occurred experience. Therefore, the system cannot conclude a rising danger of dialogue abortion only from one negative emotion observation. However, ongoing negative observations could indicate a risk of dialogue abortion.

In Gebhard [2005] a mapping of emotions into the pad-space was introduced, see Tab. 1.

In contrast to emotions, moods reflect medium-term affects, generally not related to a concrete event, cf. Morris [1989]. Moods last longer and are more stable affective states tha emotions and influence the user's cognitive functions directly. In Mehrabian [1996b] the eight octands of the pad-space are correlated with distinct mood categories, see Tab. 2.

Tab. 2. Mood terms for the pad-space.

PAD	mood	PAD	mood
+++	Exuberant	- - -	Bored
++-	Dependent	- -+	Disdainful
+-+	Relaxed	-+-	Anxious
+- -	Docile	-++	Hostile

Personality reflects the long-term affect and individual differences in mental characteristics. A common model to characterize personality is the "Five Factor Model", consisting of the "Big Five"-factors. The "Big Five"-factors describe five broad dimensions of personality. Initial work on the theory of the Five Factor Model has been published by Allport and Odbert, who used a lexical approach to find essential personality traits through language terms. Through factor analysis Allport and Odbert could identify five very strong, independent factors, the "Big Five" Allport and Odbert [1936]. Based on these findings of Allport and Odbert, Costa and McCrae [1985] developed the NEO five-factor personality inventory.

The NEO five-factor personality inventory is a multidimensional personality inventory, which includes five key factors for the "general population", focusing on the non-clinical environment: (a) Openness, (b) Conscientiousness, (c) Extraversion, (d) Agreeableness, (e) Neutricism.

The Neo five-factor personality inventory is objective, reliable and valid and generally accepted in the research community.

Mehrabian [1996b] presented a relationship between the Big Five personality traits and the pad-space:

$$p := 0.21 \cdot Extraversion + 0.59 \cdot Agreeableness + 0.19 \cdot Neutricism \tag{1}$$

$$a := 0.15 \cdot Openness + 0.30 \cdot Agreeableness - 0.57 \cdot Neutricism \tag{2}$$

$$d := 0.25 \cdot Openness + 0.17 \cdot Conscientinousness + 0.60 \cdot Extraversion - 0.32 \cdot Agreeableness \tag{3}$$

A common representation scheme is the Five Factor Model of Personality (cf. McCrae and John [1992]), using five traits to specify a general behaviour. A predicted user mood in combination with the user's personality can be used to draw conclusions about the future course of the conversation and the risk of dialogue-abortion, cf. Davidson [1994].

Extraversion is of special interest for our investigation, as we assume that this factor can be used to adjust the presented mood model, see 3.2.

Research studies which investigated extraversion as a personality trait discovered that people with high extraversion values are more satisfied and emotional stable Pavot et al. [1990]. According to Larsen and Ketelaar [1991], extraverted persons responded stronger to positive affect than to negative affect during an affect induction experiment. Furthermore, Tamir [2009] claims that extraverted persons regulate their affective states more efficiently, showing a slower decrease of positive affect. The integration of this effect into our model is shown in section 3.2.

We combine recognized emotions and given personality traits to model the user's mood to predict the progress of the Human-Machine-Interaction (HMI). We see the observed emotions as indicators that will change the systems representation of a users' mood. Together with the personality information we are able to reliably measure the risk of an interaction abortion. However, we must rely on the existing studies regarding the questions of how to represent emotions, moods and personality traits.

As stated in the previous section, emotions can either be illustrated via categories or placed in to a dimensional space. Mehrabian also located moods within the pad-space Mehrabian [1996a] and also presented a mapping between the big five personality traits and the pad-space Mehrabian [1996b].

3. MOOD MODEL IMPLEMENTATION

As stated in the the previous section, we rely on the users' mood to get an indicator of the disposition during HCI. However, it is not known how to deduce a user's mood directly. Hence, the mood has to be derived implicitly from observed emotions and should only be regarded as an approximation.

The following questions are of special importance for our model:

- How to describe mood transitions for a user.
- How to incorporate personality traits.

3.1 Modelling mood development

To answer the first question, we model the user's mood by deriving it from the measured emotions. In our model, emotions represent the observation of single short term events and are located in the pad-space.

Emotions perform a force on the mood, which is then shifted accordingly within the pad-space. In contrast to Gebhard [2005], we do not rely on a computational model, such as OCC (cf. Ortony et al. [1990]).

An abstract definition of mood in terms of pad allows our model to be independent of the chosen recognition modality. For a first approach, labelled emotions are located in pad-space based on their label. In our second approach, an underlying emotion-model allows a location of the feature-based emotions in pad-space, giving more precise results. In this paper we focus on the mood modelling rather than the emotion modelling, hence the first approach is used.

To illustrate the impact of recognized emotions on mood, we modelled the observed emotions e at time t as forces F_t^e. The force F_t^e is used to update the mood M by calculating ΔL_M, utilizing the previous damping D_{t-1}. The current damping D_t is updated by using the current emotion force F_t^e and the previous damping D_{t-1}. To decrease the effect of a single emotion force, this effect is weakened by a distinct modifiable damping term D. The following terms model the indirect impact of emotions to mood changes:

$$F_t^e = \kappa_0 \cdot e_t \tag{4}$$

$$\Delta L_M = \frac{F_t^e}{D_{t-1}} \tag{5}$$

$$M_t = M_{t-1} + \Delta L_M \tag{6}$$

$$D_t = f(F_t^e, D_{t-1}, \mu_1, \mu_2) \tag{7}$$

The modifiable damping of the mood is calculated according to Eq. 8–9. The damping is changed in each step through ΔD_t, which is a function of the observed emotion force F_t^e. The underlying function has the behaviour of a tanh-function, with the two parameters μ_1 and μ_2. μ_1 changes the oscillation behaviour of the function and μ_2 adjusts the range of values towards the maximum Damping.

$$D_t = D_{t-1} + \Delta D_t \tag{8}$$

$$\Delta D_t = \mu_2 \cdot \tanh(F_t^e \cdot \mu_1) \tag{9}$$

Since emotions and moods are represented in pad-space, our model parameters should be represented within this space as well. The emotion e_t, the emotional force F_t^e, the mood M_t, and the damping D_t are represented as pad-vectors. The mood calculation is done independently for each dimension and the result is formed from the combination of the single dimensional values.

$$\boldsymbol{e}_t = \begin{pmatrix} e_t^p \\ e_t^a \\ e_t^d \end{pmatrix}, \boldsymbol{F}_t^e = \begin{pmatrix} F_t^p \\ F_t^a \\ F_t^d \end{pmatrix}, \boldsymbol{D}_t = \begin{pmatrix} D_t^p \\ D_t^a \\ D_t^d \end{pmatrix} \ \& \ \boldsymbol{M}_t = \begin{pmatrix} M_t^p \\ M_t^a \\ M_t^d \end{pmatrix} \tag{10}$$

The mood modelling is illustrated in Fig. 3.

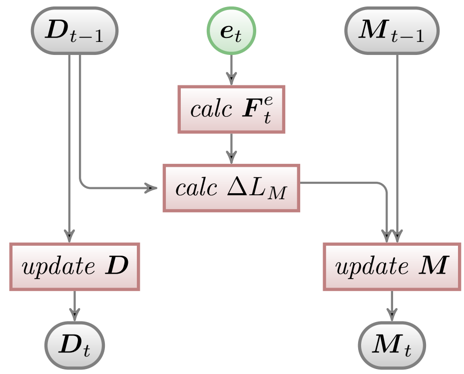


Fig. 3. Scheme of our mood model. Grey circles are inner model values, the green circle is an observed emotion, red boxes are calculations.

3.2 Mood development considering personality traits

In the previous section we explained that a user's mood is the result of the influence of the user's emotions over time with respect to the previous mood. The user's "initial mood" and the impact of the user's emotions on his/her mood depend on the user's personality traits. Hence these must be considered in the mood development model.

We chose to investigate the two impacts on the mood perception stated in Mehrabian [1996b] and Gebhard [2005]: (i) Determining an initial mood and (ii) translating the observed emotion into an emotional force.

Different users can have individual attitudes towards technical systems caused in parts by their different personalities, which can be represented by the Five Factor Model. In Mehrabian [1996a] a mapping of these personality traits into the pad-space is presented. We use this representation and place the initial mood analogue to the mapping introduced by Mehrabian [1996b].

Congruent with Larsen and Fredrickson [1999], we noticed that observed emotions, although similar in intensity and category, may be experienced differently by different users. Furthermore, depending on the user's personality, the way emotions are presented may vary. Hence, a translation of the observed emotion into the internal representation is needed. Focusing on the intensity we are using a factor to determine the difference between observation and internal feeling of the user's emotion.

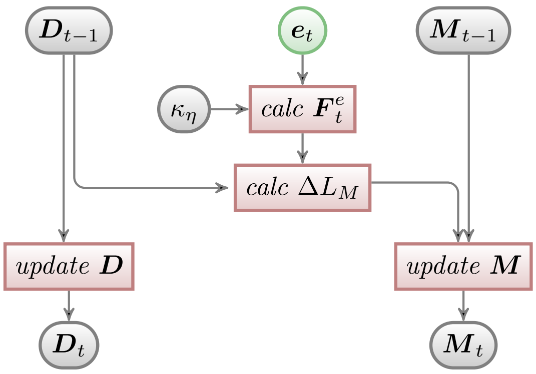


Fig. 4. Scheme of our mood model, including κ_η to infer personality traits dependent emotion force.

To adjust the factor κ_η (see Fig. 4), we rely on the values of extraversion. As explained earlier in this paper, the personality trait extraversion is particularily useful to divide subjects into the groups of a) persons "showing" emotions and b) persons "hiding" emotions. Additionally persons with high extraversion values are more stable on positive affects. This leads to a sign-dependent factor, where we distinguish between positive or negative values for emotional dimensions. This factor is used to weight positive and negative values according to the individual extraversion value of the participant. For participants with high extraversion value (≥ 0.5), $\kappa^{\text{ pos}} \geq \kappa^{\text{ neg}}$, for introverted participants (low extraversion, < 0.5) $\kappa^{\text{ pos}} < \kappa^{\text{ neg}}$.

$$\kappa_\eta = \begin{pmatrix} \kappa^{\text{ pos}} \\ \kappa^{\text{ neg}} \end{pmatrix} \tag{11}$$

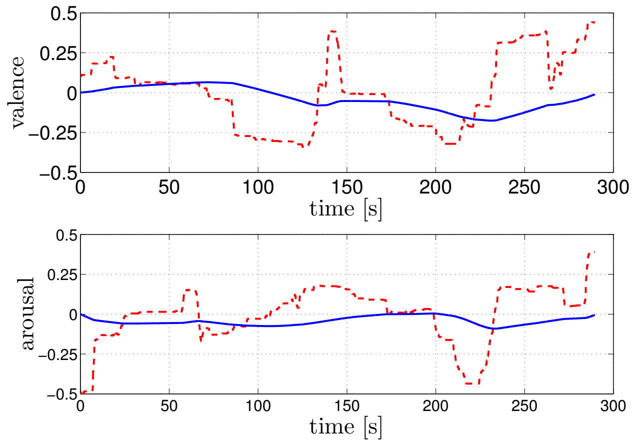
4. EXPERIMENTS

Our modelling technique needs sequences of emotion values to allow a mood prediction. As this type of data is hard to obtain, we chose two different databases that already contain emotion sequences or could be processed easily. We used two different experiments to test our model. The first experiment is an evaluation and plausibility test.

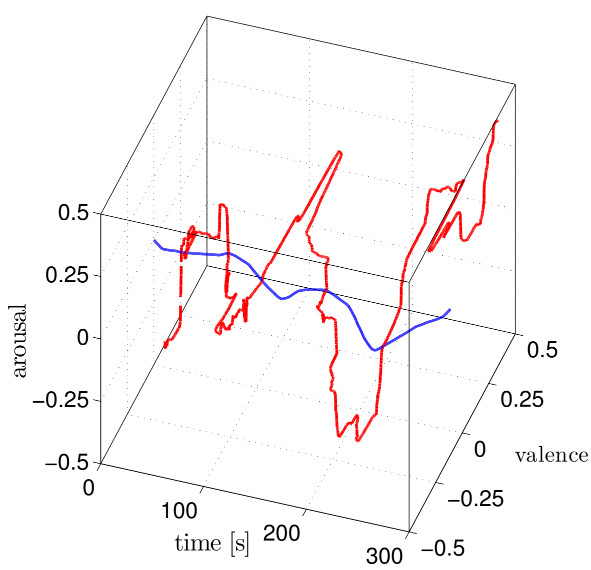
4.1 Model evaluation

The database used for the evaluation is the SEMAINE audiovisual database generated to build Sensitive Artificial Listener agents, able to hold an emotionally coloured conversation (cf. McKeown et al. [2012]). The recorded user interactions were done using the developed system of communicatively competent agents. The gathered high quality recordings consist of high-resolution video material and four microphones, recorded synchronously. For our investigations we concentrate on the transcriptions and annotations. The data was labelled on five core dimensions using GTrace, a successor to FEELtrace: (a) valence, (b) activation, (c) power, (d) anticipation/expectation, (e) intensity.

The given data can be used to show that our model is able to process emotion sequences and comes to a clear decision. We used two of the five core dimensions: valence and activation. Before using them, we calculated the mean of available annotation traces per dimension, see Fig. 5.



(a) Separated dimensions for value and arousal.



(b) Combined valence-arousal space.

Fig. 5. Mood development over time in valence-arousal space. Predicted mood as blue curve, pre-given dimension values as dashed red line.

The second corpus, EmoRec-Woz I (cf. Walter et al. [2011]), was generated during a Wizard-of-Oz experiment where the users had to play games of concentration (Memory). It contains audio, video, and bio-physiological data. Each experiment was divided into two rounds with several experimental sequences (ESs). The experiment was designed in such a way that different emotional states were induced through feedback, wizard responses and game difficulty level. The corpus contains 10 sessions for both rounds of about 30 minutes length. During the experiment the user passed several octands in the PAD-space. The ESs and expected PAD octands are shown in Tab. 3.

4.2 Infer personality traits

When including personality traits, the following must be given: Informations regarding the personality of the par-

Tab. 3. Sequence of ES and expected PAD-positions.

ES	Intro	1	2	3	4	5	6
PAD	all	+++	+-+	+-+	-+-	-+-	+-+

ticipants, informations regarding their subjective feelings and a sequence of emotions. The first prerequisites are fulfilled by EmoRec-Woz I. To gather the emotion data we must rely on labels, as it still difficult to achieve a reliable emotion recognition over time for non-acted data. For the labeling we relied on GTrace (cf. Cowie et al. [2011]), the label tool also used for the SEMAINE database. ES2 and ES5 were the most interesting sequences of the experiment, hence we concentrated on these ESs. In Fig. 6, the underlying labels for both ESs, together with the resulting mood are given.

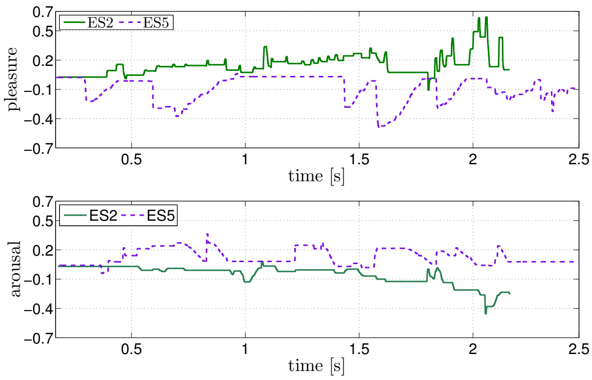


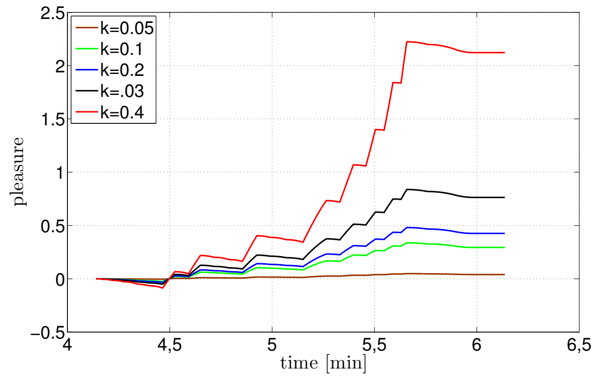
Fig. 6. Gathered average labels for dimension pleasure and arousal, utilizing GTrace for ES2 and ES5.

To integrate personality traits in our model we had to adjust two values: The initial mood M_0 and the adjustment factor κ_η.

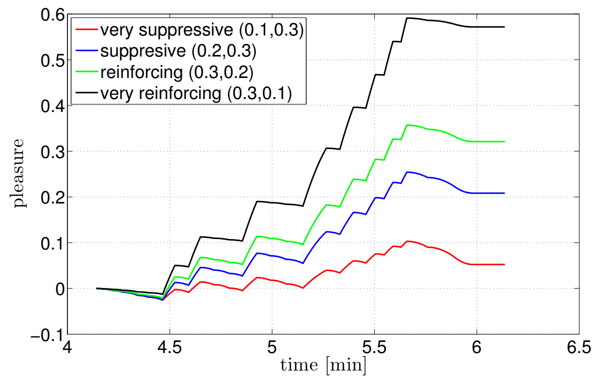
To obtain the initial mood, we calculate the translation of the personality traits into pad-space, using the results from the German NEO-FFI questionnaire, cf. Borkenau and Ostendorf [2008], according to the equations 1 – 3 formulated by Mehrabian [1996b], see Tab. 4. If we compare these results with the labels gathered via GTrace, we notice, that the moods differ from our calculated initial mood at the beginning of the experimental sequences. This is due the fact that there is a short pause between each sequence of about 5s where the labelers assume that the participants are calm.

We adjusted κ_η according to our suggested implementation. We chose different values for κ, reaching from 0.05 to 0.4, see Fig. 7(a). Values higher than 0.3 led to the mood raising too fast, hence values ¿ 0.3 should be avoided. According to our suggested implementation, we also tested different settings for the difference between $\kappa^{\text{ pos}}$ and $\kappa^{\text{ neg}}$. We noticed that small differences are more promising (see Fig. 7(b)) and comparable to the participants assessment. The chosen values for selected participants are given in Tab. 4.

Fig. 7(a) shows that high values of κ led to unplausible moods. In contrast, very small values let the mood become



(a) Different κ_η values, for mood calculation, not differ between $\kappa^{\text{ pos}}$ and $\kappa^{\text{ neg}}$.



(b) Different adjustments of $\kappa^{\text{ pos}}$ and $\kappa^{\text{ neg}}$.

Fig. 7. Mood development for different settings of κ_η, considering only pleasure dimension for ES2, minimized influences of the damping.

Tab. 4. Calculated pad-values/initial moods for selected participants using NEO-FFI results, their Extraversion (E) and resulting κ.

Participant	p	a	d	E	$\kappa^{\text{ pos}}$	$\kappa^{\text{ neg}}$
602	0.59	0.04	0.36	0.5	0.3	0.2
226	0.77	0.31	0.54	0.83	0.2	0.2
518	0.50	-0.02	0.18	0.22	0.2	0.3

insensitive for emotional changes. Values in the range from 0.1 to 0.3 seem to provide a comprehensible mood course.

In ES1, ES2, ES3, and ES6 mostly positive emotions, in ES4 and ES5 mostly negative emotions were induced. Investigations with emotion recognizers using prosodic, facial and bio-physiological features (cf. Walter et al. [2011]) and the comparison to the experimental design support the emotional course. As we could not give a realistic examination for all emotions, we concentrated on the "pleasure"-dimension, as for this secured studies are available. Using this data as input to our presented mood model, we were able to show, that our model follows the prediction for pleasure of given ESs in the experiment, see Fig. 8.

In the beginning of ES1 the mood rests in its initial position and it takes some time-steps, until the mood starts to shift towards the positive region. In ES2, and ES3

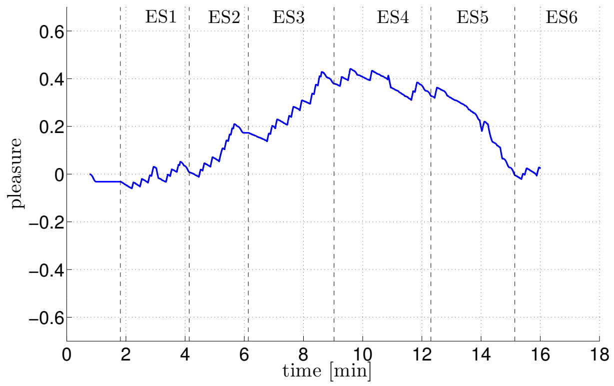


Fig. 8. Evaluation of proposed mood model using emotions gathered via an appraisal process.

the mood continues to rise. During ES4, when inducing more negative emotions due to negative feedback and time pressure, the mood slowly sinks. At the end of the negative ES5 the mood is negative, which continues untill the beginning of ES6. Furthermore, during the course of ES6, where many positive emotions are induced, it is possible to change the mood again towards positive pleasure values.

5. DISCUSSION AND CONCLUSION

In this paper we presented our suggested mood modelling technique. After giving some fundamental and needed psychological background, we described our derived implementation. Our model is intended to reproduce the mood development over time using emotional assessment. We were able to evaluate the principal function of our model with two different databases. In comparison to the already evaluated experimental course of the second corpus, we were able to show that our model generated a mood course which matched the experimental setting.

As mentioned in section 3.1, the presented results are based on labelled emotions, located in pad-space according to their label. In section 3.1 we mentioned a second approach, where the user's mood is derived from the measured emotions, using an underlying emotion model. This emotion model allows the label-independent investigation and location of emotions in pad-space. Instead of locating an emotion according to its label, the emotion is located in pad-space according to its features (given in terms of pad). This allows a more precise, feature-based location of emotions in pad, as it avoids the deviations that may arise due to expert-based labelling. Furthermore it allows the identification of the precise emotion coordinates, rather than choosing a point of an emotion area. The named model will be further discussed in a follow-up paper of the group.

Another problem that has to be addressed is the need of equally distributed values over time. So far the emotional assessments are processed without regarding a gap between them, but this cannot be guaranteed especially when using recognised emotion values. Here a further extension of our model is needed, for example by temporal averaging or weighting.

ACKNOWLEDGEMENTS

This work was done within the Transregional Collaborative Research Centre SFB/TRR 62 "Companion-Technology for Cognitive Technical Systems" funded by the German Research Foundation (DFG).

REFERENCES

G.W. Allport and H.S. Odbert. Trait-names, a psycholexical study. *Psychological Monographs*, 47(1):i–171, 1936.

E. André, M. Klesen, P. Gebhard, S. Allen, and T. Rist. Integrating Models of Personality and Emotions into Lifelike Characters. In *Affective interactions: towards a new generation of computer interfaces*, volume 1814 of *Lecture Notes in Computer Science*, chapter 11, pages 150–165. Springer, Berlin, Heidelberg, 2000.

A. Batliner, S. Steidl, B. Schuller, D. Seppi, T. Vogt, J. Wagner, L. Devillers, L. Vidrascu, V. Aharonson, L. Kessous, and N. Amir. Whodunnit – Searching for the Most Important Feature Types Signalling Emotion-Related User States in Speech. *Computer Speech and Language*, 25(1):4–28, 2011.

P. Becker. Structural and relational analyses of emotions and personality traits. *Zeitschrift für Differentielle und Diagnostische Psychologie*, 22(3):155–172, 2001.

P. Borkenau and F. Ostendorf. *NEO-Fünf-Faktoren-Inventar. (NEO-FFI) nach Costa und McCrae*. Hogrefe, Göttingen, 2 edition, 2008.

C. Busso, Z. Deng, S. Yildirim, M. Bulut, C.M. Lee, A. Kazemzadeh, S. Lee, U. Neumann, and S. Narayanan. Analysis of emotion recognition using facial expressions, speech and multimodal information. In *Proc. of the 6th International Conference on Multimodal Interfaces*, pages 205–211, New York, USA, 2004. ACM.

P.T. Costa and R.R. McCrae. *The NEO Personality Inventory manual*. Psychological Assessment Resources, Odessa, USA, 1985.

R. Cowie, C. Cox, J.-C. Martin, A. Batliner, D. Heylen, and K. Karpouzis. Issues in Data Labelling. In R. Cowie, C. Pelachaud, and P. Petta, editors, *Emotion-Oriented Systems: The Humaine Handbook*, Cognitive Technologies, pages 213–241. Springer Verlag, London, UK, 2011. URL `http://doc.utwente.nl/79619/`.

R.J. Davidson. On emotion, mood, and related affective constructs. In Paul Ekman, editor, *The nature of Emotion: Fundamental Questions*, pages 51–56. Oxford University Press, Oxford, UK, 1994.

P. Ekman. *Basic Emotions*, pages 45–60. John Wiley & Sons, Ltd, Sussex, UK, 2005.

P. Gebhard. ALMA A Layered Model of Affect. In *4th International Joint Conference of Autonomous Agents & Multi-Agent Systems*, pages 29–36, Utrecht, The Netherlands, July 25-29 2005. ACM.

T. Gehm and K.R. Scherer. Factors determining the dimensions of subjective emotional space. In K.R. Scherer, editor, *Facets of emotion: Recent research*, pages 99–114. NJ: Erlbaum, Hillsdale, USA, 1988.

K. Hartmann, I. Siegert, S. Glüge, A. Wendemuth, M. Kotzyba, and B. Deml. Describing Human Emotions Through Mathematical Modelling. In *Proceedings of the MATHMOD 2012 - 7th Vienna International Con-*

ference on Mathematical Modelling, Vienna, Austria, February 15-17 2012.

S. Kopp, L. Gesellensetter, N.C. Krämer, and I. Wachsmuth. *A conversational agent as museum guide: design and evaluation of a real-world application*, pages 329–343. Springer, Berlin, Heidelberg, 2005.

M. Kotzyba, B. Deml, H. Neumann, S. Glüge, K. Hartmann, I. Siegert, A. Wendemuth, H. Traue, and S. Walter. Emotion Detection by Event Evaluation using Fuzzy Sets as Appraisal Variables. In N. Ruwinkel, U. Drewitz, and H. van Rijn, editors, *Proceedings of the 11th International Conference on Cognitive Modeling*, Berlin, Germany, April 13-15 2012. Universitätsverlag der TU Berlin.

R.J. Larsen and B.L. Fredrickson. Measurement Issues in Emotion Research. In D. Kahneman, E. Diener, and N. Schwarz, editors, *Well-being: Foundations of hedonic psychology*, pages 40–60. Russell Sage Foundation, New York, USA, 1999.

R.J. Larsen and T. Ketelaar. Personality and susceptibility to positive and negative emotional states. *Journal of Personality and Social Psychology*, 61:132–140, 1991.

R.R. McCrae and O.P. John. An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, 60(2):175–215, 1992.

W. McDougall. *An introduction to social psychology*. J.W. Luce & Co, London, UK, 1919/2001.

G. McKeown, M. Valstar, R. Cowie, M. Pantic, and M. Schroder. The SEMAINE Database: Annotated Multimodal Records of Emotionally Colored Conversations between a Person and a Limited Agent. *Affective Computing, IEEE Transactions on*, 3(1):5 –17, jan.-march 2012.

A. Mehrabian. Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. *Current Psychology*, 14(4): 261–292, 1996a.

A. Mehrabian. Analysis of the Big-five Personality Factors in Terms of the PAD Temperament Model. *Australian Journal of Psychology*, 48(2):86–92, 1996b.

A. Mehrabian and J.A. Russell. Evidence for a three-factor theory of emotions. *Journal of Research in Personality*, 11:273–294, September 1977.

W.N. Morris. *Mood: the frame of mind*. Springer, New York, 1989.

A. Ortony, G.L. Clore, and A. Collins. *The Cognitive Structure of Emotions*. Cambridge University Press, Cambridge, UK, 1990.

W. Pavot, E. Diener, and F. Fujita. Extraversion and happiness. *Personality and Individual Differences*, 11: 1299–1306, 1990.

R.W. Picard. *Affective Computing*. MIT Press Cambridge, 2000.

R. Plutchik. *Emotion, a psychoevolutionary synthesis*. Harper & Row, New York, 1980.

J.A. Russel. Three dimensions of emotion. *Journal of Personality and Social Psychology*, 39(9):1161–1178, December 1980.

J.A. Russel and A. Mehrabian. Distinguishing anger and anxiety in terms of emotional response factors. *Journal of Consulting and Clinical Psychology*, 42:79–83, 1974.

K.R. Scherer, E. Dan, and A. Flykt. What determines a feeling's position in affective space? A case for appraisal. *Cognition and Emotion*, 20:92–113, 2006.

H. Schlosberg. Three dimensions of emotion. *Psychological Review*, 61(2):81–88, 1954.

M. Tamir. Differential preferences for happiness: Extraversion and trait-consistent emotion regulation. *Journal of Personality*, 77:447–470, 2009.

S. Walter, S. Scherer, M. Schels, M. Glodek, D. Hrabal, Miriam Schmidt, R. Böck, K. Limbrecht, H. Traue, and F. Schwenker. Multimodal Emotion Classification in Naturalistic User Behavior. In Julie Jacko, editor, *Human-Computer Interaction. Towards Mobile and Intelligent Interaction Environments*, volume 6763 of *Lecture Notes in Computer Science*, pages 603–611. Springer, Berlin, Heidelberg, 2011.

A. Wendemuth and S. Biundo. A Companion Technology for Cognitive Technical Systems. In *Cognitive Behavioural Systems*, Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, 2012. in press.

W.M. Wundt. *Vorlesungen über die Menschen- und Tierseele*. L. Voss, Leipzig, 1922/1863.