Towards a Unified 3D Affective Model

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Abstract. The nowadays affective models consider either a number of discrete affective states or a continuous space of affective states. In this paper we propose a fuzzy logic-based extension to the continuous 2D activation-evaluation affective model and a quantization methodology to define the areas of the discrete sets of basic affective states that unifies the discrete and dimensional models. We demonstrate why a third dimension (intensity) is useful to be added to the activation-evaluation model. The advantages of the new model are the ability to define basic affective states areas in the activation-evaluation plane, the personalization, the ability to express the secondary states as nuances of the basic affective states and to explicitly express the intensity of each state. A new methodology using statistics is proposed in order to construct a generalized and a personalized affective model.

Keywords: Affective Modelling, Fuzzy Logic, statistics.

1 Introduction

The following scenario illustrates the problem that we envision in an affective aware system: "Jane is back home from her job. She is a little tired but very content as her daily tasks went well. A specially designed device detects her affective state as being somewhere between these two states (tiredness and contentment), near to the 'relax'. Her smart house is now aware of her affective state and chooses an appropriate multimedia file from a rich-in-items distant multimedia database for Jane's scheduled entertainment hour. She sees the top 10 search results and makes her choice."

Some questions issue from this scenario:

1. What affective model to use when communicating affective states to a distant artificial system (or person) and why?
2. What are the affective model's attributes to be sent and used by the server side in order to choose the most appropriate item for the user's affective state?
3. How can we personalise the affective model?

In the next section we motivate our choice on the activation-evaluation affective model. We explain the proposed activation-evaluation-intensity affective model in section 3. In Section 4 we describe the methodology used in building the proposed model. In Section 5 we demonstrate that the intensity of an affective state is not proportional to the distance from the activation-evaluation axis origin as previously supposed. We address related works in Section 6. And finally in the last section we give some conclusions and briefly speak about further developments.

2 The State of the Art in Affective Models

There are many affective models that mainly can be classified into two classes: a) discrete affective states vector [1][2][3][4]; b) 2 dimensional [5][6] or 3 dimensional [7] continuous affective space. We answer the first question from Section 1 saying that the well-known 2D activation-evaluation plane originating in [8] and used in [9] is more precise and general than the discrete affective states vector as it allows a smooth passage from one state to another in an infinite set of values. But the actual affective states detectors usually use a discrete set of (basic, defined later in this paragraph) states classifying among them the one that is best rated. We aim to map the (basic) affective states areas in the activation-evaluation plane thus unifying the two main affective model classes (discrete and dimensional).

Another issue of the activation-evaluation model is that it does not allow explicitly expressing the intensity of the affective state as it is supposed being already present in the model (it increases from zero in the origin to ±1 on the circumference, along the radius) [9], but never proved by dedicated experiments. Even if we would agree that the intensity of a state is implicit in the model, one can ask for instance: how much would take to happiness to become ecstasy? Is there any measure like "very" means +0.2 of +1 on the evaluation axis and +0.1 of +1 on the activation axis?

In the theory of emotions there are the notion of basic emotion (or affective state) and secondary emotion (or affective state). The basic affective states are defined in [8] as follows: *"Within the framework of the theory a basic or primary emotion is one that is identifiable at all phylogenetic levels, including humans, and has adaptive significance in the individual's struggle for survival. Eight such basic or 'prototypic' patterns of emotion are described; it is then possible to show systematically that mixtures of two or more primary emotions produce the many hundreds of mixed emotions we encounter in daily life and clinical practice. All individual differences in the emotional realm can thus be conceptualized as the overt expression of combinations of eight basic dimensions"*. However there are a few works [2][8] or based on experiments with a very few people (five in [2]) that define the exact values of the relations between the secondary and the basic emotions. Moreover they do not cover the personalisation issue, as each person is unique and can have different values for the relations between the secondary and the basic emotions. We search for a methodology to define the values for these relations and to construct a personalised affective model.

3 The Proposed Activation-Evaluation-Intensity Affective Model

In this paper we continue the work on modelling affective states for context-aware applications as started in [10], where we proposed a generic 3D affective model starting from the activation-evaluation plane (see Fig. 1) by giving a methodology to define basic affective areas inside the activation-evaluation plane and motivating the utility of the intensity axis.

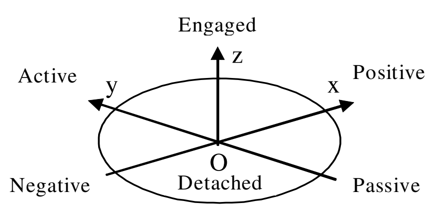


Fig. 1. The three axes affective model; the intensity axis represented as a detachment-engagement dipole, 'Detached' represents no emotion and 'Engaged' indicates towards the maximum intensity.

In modelling user's affective states the requirements for the model, as discussed in the above chapter, are the following:

- To allow the definition of distinct states in the continuous affective space.
- To express the secondary states as nuances of the (distinct) basic states.
- To allow the personalization of the affective model.
- To allow explicitly expressing the intensity of each state

The formal description of the model consists in a set of fuzzy sets corresponding to the basic states on each of the three axes for the individual model and another set for the generalized one:

S1. We represent the basic affective states in a three dimensional space: activation (Oy), evaluation (Ox) and intensity (Oz).

S2. Each secondary affective state is a point in the activation-evaluation space and is characterized by a fuzzy set, more precisely, by the membership degree (called also membership function) of the fuzzy set. The intensity axis is divided in three regions corresponding to the fuzzy set for low, medium and high.

S3. We propose two different methods to define the fuzzy sets, i.e. their membership functions. Using the data obtained from applying a test (that is described in the next section) to N persons and considering n basic affective states we can construct a "personal affective model" (for each person) and a "general affective model".

The proposed model answers the questions 2 and 3 from Section 1 as the membership degree correlates the personal and general affective model values when transmitting the data from the server to the client. In our scenario, when Jane's state has certain coordinates in her personal affective model, these will be transformed into certain membership degrees that have a correspondence in the general affective model and thus a nearest item will be selected.

In the following section we describe how to construct the model using fuzzy sets to characterize each of the basic states on the activation-evaluation plane.

4 Affective Model Building Methodology

Let $\{\Psi_{j:}\ j=1,n\}$ be the set of all basic emotions, where n is the total number of basic states considered in the model [11] (we consider here the 6+1 from facial expressions: anger, disgust, fear, joy, sadness, surprise [1] and neutral). Let N be the total number of persons involved in the random sample for this test.

First Method

The *personalized model* for the i-th tested person (i=1,…,N):

- On the evaluation axis Ox we define the membership degree for the state Ψj for the i-th person

$$\mu_{i,j}(x) = \begin{cases} 0,\ x \le a_{ij} \\ (x - a_{ij})/(b_{ij} - a_{ij}),\ x \in (a_{ij}, b_{ij}] \\ (c_{ij} - x)/(c_{ij} - b_{ij}),\ x \in (b_{ij}, c_{ij}) \\ 0,\ x \ge c_{ij} \end{cases}. \qquad (1)$$

where:

a_{ij}= minimum of all Ox values obtained from the data corresponding to i-th person for the state Ψ_j,
b_{ij}= mean value of all Ox values corresponding to the i-th person for the state $\Psi_{j,}$
c_{ij}= maximum of all Ox values obtained from the data corresponding to i-th person for the state Ψ_j .

-On the activation axis Oy we define the membership degree for the state Ψ_j for the i-th person

$$\nu_{i,j}(y) = \begin{cases} 0,\ y \le d_{ij} \\ (y - d_{ij})/(e_{ij} - d_{ij}),\ y \in (d_{ij}, e_{ij}] \\ (f_{ij} - y)/(f_{ij} - e_{ij}),\ y \in (e_{ij}, f_{ij}) \\ 0,\ y \ge f_{ij} \end{cases}. \qquad (2)$$

where:

d_{ij} =minimum of all Oy values obtained from the data corresponding to i-th person for the state Ψ_j,
e_{ij}= mean value of all Oy values corresponding to the i-th person for the state Ψ_j,
f_{ij}= maximum of all Oy values obtained from the data corresponding to i-th person for the state Ψ_j .

The *general model* (we use the data obtained from all N tested persons):

- On the evaluation axis Ox we define the membership degree for the state Ψj

$$\mu_{j}(x) = \begin{cases} 0,\ x \le A_{j} \\ (x - A_{j})/(B_{j} - A_{j}),\ x \in (A_{j}, B_{j}] \\ (C_{j} - x)/(C_{j} - B_{j}),\ x \in (B_{j}, C_{j}) \\ 0,\ x \ge C_{j} \end{cases}. \qquad (3)$$

where:
A_j =min{a_{ij}: i=1,…, N}, B_j =(b_{1j}+b_{Nj})/N, C_j=max{c_{ij}: i=1,…,N}.

- On the activation axis Oy we define the membership degree for the state Ψj

$$\nu_j(y) = \begin{cases} 0, \; y \le D_j \\ (y - D_j)/(E_j - D_j), \; y \in (D_j, E_j] \\ (F_j - y)/(F_j - E_j), \; y \in (E_j, F_j) \\ 0, \; y \ge F_j \end{cases} . \quad \textbf{(4)}$$

where:
D_j = min{d_{ij}: i=1,…, N}, E_j =(e_{1j}+…e_{Nj})/N , F_j =max{f_{ij}: i=1,…, N }.

Second Method

We show how we compute the values A_j and C_j by using *the method of confidence intervals for theoretical mean* (denoted by M_j) of a random sample which follows an unknown distribution, but for which we have sufficiently many observations (more than 30) (see [12], p. 381). To use this method in this special context is new.

For the generalized model let $x_{1,j},\ldots,x_{p,j}$ be the coordinates (on the Ox axis) obtained from all N tested persons for the emotional state Ψ_j (p>30). We consider the sample mean

$$\overline{X_j} = \frac{1}{p}\sum_{k=1}^{p} x_{k,j} . \quad \textbf{(5)}$$

and sample variance

$$\overline{S_j^2} = \frac{1}{p-1}\sum_{k=1}^{p}(x_{k,j} - \overline{X}_j)^2 . \quad \textbf{(6)}$$

The statistics

$$T_j = \frac{\overline{X_j} - M_j}{\frac{\overline{S_j}}{\sqrt{p}}} . \quad \textbf{(7)}$$

has Student distribution with p-1 degrees of freedom and we denote by F_{p-1} its distribution function. Let $\alpha \in (0,1)$ be the significance level (in our applications α=0.00001). We determine the quantile t of order 1-α/2 for this distribution, i.e. t=F_{p-1}^{-1}(1-α/2)=*tinv*(1-α/2,p-1) (*tinv* is the command used in Matlab Statistics Toolbox). This implies that the statistics T_j takes values in the interval [-t, t] with probability 1-α, which implies

$$P\left(\overline{X_j} - t\frac{\overline{S_j}}{\sqrt{p}} \le M_j \le \overline{X_j} + t\frac{\overline{S_j}}{\sqrt{p}}\right) = 1 - \alpha . \quad \textbf{(8)}$$

In our application we consider the lower bound

$$A_j = \overline{X_j} - t\frac{\overline{S_j}}{\sqrt{p}} = \frac{1}{p}\sum_{k=1}^{p} x_{k,j} - t\sqrt{\frac{1}{p(p-1)}\sum_{k=1}^{p}\left(x_{k,j} - \frac{1}{p}\sum_{k=1}^{p} x_{k,j}\right)^2} \quad . \qquad \textbf{(9)}$$

and the upper bound

$$C_j = \overline{X_j} + t\frac{\overline{S_j}}{\sqrt{p}} = \frac{1}{p}\sum_{k=1}^{p} x_{k,j} + t\sqrt{\frac{1}{p(p-1)}\sum_{k=1}^{p}\left(x_{k,j} - \frac{1}{p}\sum_{k=1}^{p} x_{k,j}\right)^2} \quad . \qquad \textbf{(10)}$$

Note that the theoretical mean M_j of all coordinates of the Ox axis for the state ψ_j, takes with probability 1-α values in the interval $[A_j, C_j]$.

Using the function *tinv* from Matlab Statistics Toolbox and considering a random sample of size *N*=31, and 31 values for the Ox coordinates for a certain emotional state (the test contained 31 images for each state; all 31*7 images for the 7 states were shown randomly), we get *p*=31*31, and the quantile *t* of order 1-α/2 is

t= *tinv*(1-0.00001/2,31*31-1) = 4.4409 . **(11)**

The same ideas we use to determine the confidence interval for the mean of the coordinates on the Oy axis, and also for determining the intervals $[a_{ij}, c_{ij}]$, respectively $[d_{ij}, f_{ij}]$ in the personalized model for the *i*-th person and the state ψ_j. In the personalized model for the i-th person we have *p*=31 de coordinates (from the 31 images) for a state ψ_j. By using Matlab Statistics Toolbox, we get that the quantile τ of order 1-α/2 is

τ = *tinv*(1-0.00001/2,31-1) = 5.2995 . **(12)**

With this new value we compute the lower bound

$$a_{ij} = \frac{1}{p}\sum_{k=1}^{p} x_{k,i,j} - \tau\sqrt{\frac{1}{p(p-1)}\sum_{k=1}^{p}\left(x_{k,i,j} - \frac{1}{p}\sum_{k=1}^{p} x_{k,i,j}\right)^2} \quad . \qquad \textbf{(13)}$$

and the upper bound for the mean

$$c_{ij} = \frac{1}{p}\sum_{k=1}^{p} x_{k,i,j} + \tau\sqrt{\frac{1}{p(p-1)}\sum_{k=1}^{p}\left(x_{k,i,j} - \frac{1}{p}\sum_{k=1}^{p} x_{k,i,j}\right)^2} \quad . \qquad \textbf{(14)}$$

where $x_{1,i,j},\ldots,x_{p,i,j}$ (where *p*=31) are the coordinates on the Ox axis obtained from the data of the i–th person for the state ψ_j.

In order to build the model we used the MMI database [13]. For each of the seven basic emotions (happy, sad, angry, fear, neutral, surprise and disgust) we prepared a set of 31 pictures that represent variations of the same basic state displayed by different people. A characteristic of the MMI database is the big amount of information tagged with metadata and the diversity of the people in terms of sex, age, and ethnicity.

A number of 31 persons differing in age (16-62 years old), gender (16 masculine and 15 feminine) and background participated in the test. For each of them a number of 217 (7*31) pictures representing people in different emotional states where presented in a graphical user interface written in Java (see Fig.2) in a random order. On each picture, the tested person had to evaluate the affective state of the person displaying a certain basic affective state, by clicking on the activation-evaluation plane by using a modified version of the Feeltrace tool from [9].

As the results where gathered on each person a personal affective user model similar to the one in Fig. 3 was created. Finally a general affective model based on statistics was generated. We may observe that the Oz axis is not the intensity in this figure, it is the membership degree; the complete activation-evaluation-intensity model with membership degrees for each axis would need a representation in 4 dimensions or at least different colour codes for the intensity.

Comparing the methods to define the fuzzy sets we conclude:

- The first method, that uses the average of all coordinate values on each axis is not so good, because the sets become too large.
- The second method, that uses confidence intervals is more flexible allowing to control the percent of coverage of the areas occupied by a certain state in the activation-evaluation plane (i.e. 70% of the points for happiness are in the area defined for that state if the significance level is α=0.001).

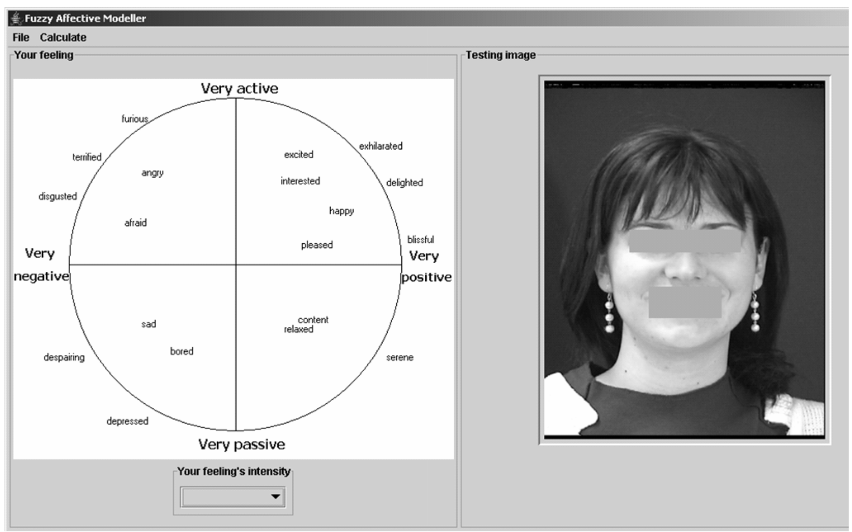


Fig. 2. The affective modeller graphic interface with the activation-evaluation plane and intensity drop box on the left side and the pictures of persons displaying affective states (from MMI database) on the right side

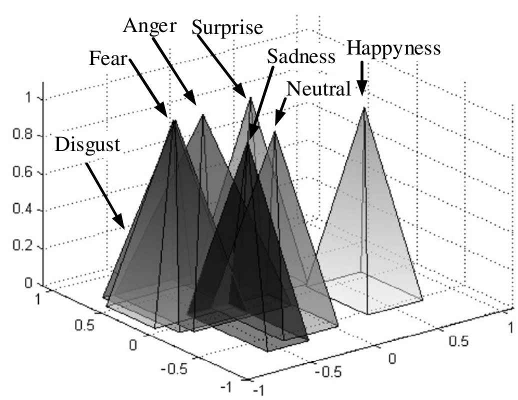


Fig. 3. An example of personal affective model, here the Oz axis is the membership degree.

5 The Intensity Axis

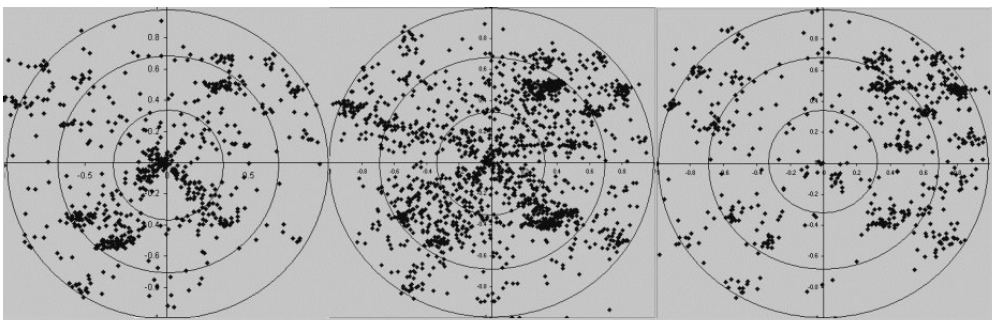
R. Plutchik postulates that "each emotion can exist in varying degrees of intensity" [9], for example we may say that somebody is not very happy, is happy, is very happy or she is the happiest person in the world. In his review on the R.W. Picard's "Affective Computing" book, A. Sloman argues that someone may have not just one affective state but a number of affective states generated by different factors [14]. In order to select the dominant affective state (or states) we have to take into account the intensity.

In the activation-evaluation model [8] it is asserted that the intensity of the state is proportional to the distance from the origin of the two axes. We researched this hypothesis as follows:

Our method consists in representing values obtained from the coordinates corresponding to a certain state and intensity (low, medium, high) given by the user for the same state, while viewing a set of 90 paintings, 31 people have participated at this test.

The results, as you may see in Fig. 3, indicate that there is no correlation, as previously supposed, (the distribution is random), one can find many coordinates for different emotional states which have low intensity even far away from the origin and so the intensity axis perpendicular to the activation-evaluation plane is needed as given in Fig.1.

We have to mention that there is a clear distinction between the intensity of an affective state and membership degree as the last one indicates how much a secondary state is a part of one of the basic affective states.



a) b) c)

Fig. 3. The distribution of points in the activation-evaluation plane for the intensity of the affective state auto-evaluated as: a) low; b) medium; c) high.

6 Related Work

The presented model, as already said, extends the activation-evaluation model from [15] by adding a third dimension justifying its utility and giving a methodology to define the area of the basic affective states.

Our proposed model differs from the 3 dimensional PAD model [7] because the third dimension in the PAD model describes the ability cu control a certain state (D from dominance) –which we ignore in our model as we consider it as being cognitive- and we think it could be itself improved with a fourth intensity dimension.

In the article [3] the authors propose a method to define four discrete regions in the arousal-valence (activation-evaluation) for dialog management (anger, stress, happy, neutral). In our work we define the basic states regions and the secondary states – basic states relations as fuzzy logic membership degrees.

The secondary states are expressed in [2] as a weighted linear combination of the basic states. The weight values are determined by giving values between –100 and 100 for each. In our proposition we use the Feeltrace like tool based on the activation-evaluation plane to define the position of the secondary affective states and the areas of the basic affective states, which is more intuitive.

In the model FLAME [16] a set of nine states affective and motivational are considered. For each of the motivational states true nuance values between 0.0 and 1.0 are assigned. Each affective state has three intensity levels (low, medium, high) expressed as fuzzy logic sets. In our model the basic affective states areas are defined using fuzzy logic in the activation-evaluation plane, the intensity of each affective state is express in the same way as in FLAME.

7 Conclusions and Further Work

The proposed model allows the representation of the secondary states in relation with the basic ones, the personalization and the ability to express the nuances of the affective states. We demonstrated the utility of the intensity axis perpendicular to the activation-evaluation plane. We proposed a new methodology using statistics for the construction of a generalized and a personalized affective model.

In the future we will implement this model in an affective aware intelligent space (smart house). We will also look for a method to optimise the proposed affective model in time according to the user's changing model of emotions, by taking into account his/her feedback.

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