A Fuzzy Modelling Approach of Emotion for Affective Computing Systems

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Keywords: Adaptive Fuzzy Systems, Emotion Modelling, Affective Trajectories, Arousal Valence, Affective Computing, Personalised Learning.

Abstract: In this paper we present a novel affective modelling approach to be utilised by Affective Computing systems. This approach is a combination of the well known Arousal Valence model of emotion and the newly introduced Affective Trajectories Hypothesis. An adaptive data driven fuzzy method is proposed in order to extract personalized emotion models, and successfully visualise the associations of these models' basic elements, to different emotional labels, using easily interpretable fuzzy rules. Namely we explore how the combinations of arousal, valence, prediction of the future, and the experienced outcome after this prediction, enable us to differentiate between different emotional labels. We use the results obtained from a user study consisting of an online survey, to demonstrate the potential applicability of this affective modelling approach, and test the effectiveness and stability of its adaptive element, which accounts for individual differences between the users. We also propose a basic architecture in order for this approach to be used effectively by AC systems, and finally we present an implementation of a personalised learning system which utilises the suggested framework. This implementation is tested through a pilot experimental session consisting of a tutorial on fuzzy logic which was conducted under an activity-led and problem based learning context.

1 INTRODUCTION

The modern world calls for techniques which enable the surrounding environment to behave in an intelligent way in order to support and aid people in their lives. Ambient Intelligence (AmI) has emerged as a discipline promising to satisfy this need through modifying our everyday environment by providing intelligence to networks of electronic devices around us. But how is it possible for this vision of AmI to be realised through the development of truly intelligent systems, if they do not possess a basic understanding of core aspects of human behavior such as emotions? Affective Computing (AC) is an emerging scientific field that incorporates emotion into the design of computing systems, in order to bridge the gap between the emotional human and the emotionally challenged computer application. Affective Computing is defined in (Picard, 1999) as "computing that relates to, arises from or deliberately influences emotions". Emotions influence almost every cognitive process of an individual. Their influence in performance, motivation, learning, communication, perception and organization of memory, attention and many other aspects of human life has been identified by numerous studies (Nasoz, 2010). Therefore as Rosalind Picard pointed out, if we wish to construct an intelligent system with a higher level of human machine interaction, we should allow them to successfully recognize and model emotions, or even enable them to express their own emotions. The range of applications of AC is vast since emotion plays a vital role in every aspect of human life. Since the dawn of AC we have seen applications in medicine (Lisetti, 2003), gaming (Mandryk, 2007), learning (Graesser, 2005), driving (Nasoz, 2010) and many others. This paper focuses especially on the application of AC in learning by presenting a personalised learning AC system. Emotion plays a vital role in the learning process due to its close relation to the levels of motivation and engagement

Karyotis, C., Doctor, F., Iqbal, R., James, A. and Chang, V.
A Fuzzy Modelling Approach of Emotion for Affective Computing Systems.
DOI: 10.5220/0005945604530460
In *Proceedings of the International Conference on Internet of Things and Big Data (IoTBD 2016)*, pages 453-460
ISBN: 978-989-758-183-0

of the learner. Therefore we can infer the need of AC systems with the ability to take emotion into account in order to aid in the educational process.

As proposed by Wu et Al in (Wu, 2010) an AC system should consist of three basic elements. These elements will be responsible for recognizing and modelling affect, and finally making the necessary shifts of user's affective states by outputting the necessary control signals (figure 1). Wu's affective loop is the basis of our proposed architecture.

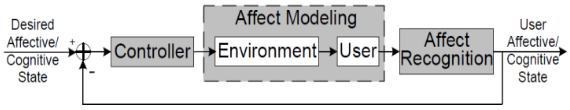

Figure 1: Wu's affective loop.

In AC one of the most important design dilemmas is the selection of the appropriate machine learning technique for modelling affect relations, and mapping low level values, such as sensory inputs, to values of affective states. Our selected machine learning and affect modelling approach is based on Fuzzy Logic. Fuzzy logic systems are very efficient in dealing with uncertainties concerning emotion (Wu, 2012). Different people may perceive or express the same emotion differently (interpersonal uncertainty), while even the same individual may have uncertainty about the same emotion in different times or in a different context (intrapersonal uncertainty). Moreover through employing fuzzy logic we can construct interpretable rule bases to illustrate the existing relations. This is fundamental for our research since we aim to be able to reveal the underlying affect relations while building an effective AC system.

Modelling and understanding emotion is a very difficult task, heavily debated by psychologists. In the early days of psychology the prominent view was that the labels we use to describe our affective state are in direct relation to underlying discrete affective states. Paul Ekman for example identified six basic emotions (anger, disgust, fear, happiness, sadness and surprise) by using cross-cultural facial expressions experiments (Ekman, 1975). A different approach called psychological constructivism, suggests that emotion is constructed from the combination of more basic elements. Examples of constructivist theories are the Arousal Valence (AV) model (Russell, 1980) and the Affective Trajectories (AT) Hypothesis (Kirkland, 2012). The arousal valence model suggests that emotions can be represented as points in a two-dimensional space where the first axis is valence, and it ranges from unpleasant to pleasant, and the second axis is arousal, and it ranges from passive to active (figure 2). For example anger can be defined as a high arousal and negative valence state. The AT hypothesis on the other hand states that an emotional experience can be created from the combination of a person's evaluation of their current state, their predictions about the future, and their evaluations of the outcome they have experienced (Kirkland, 2012). With this approach anger could be defined as a state where the outcome of a process is bad and unexpected. In (Karyotis, 2015) was shown that this approach can be used within the context of education and that individual differences play a part in the construction of different affective states. Meaning that every individual utilizes the AT's basic elements but may do so in a personalised manner.

In our research the use of the combination of these two models is suggested in order to differentiate more successfully between the emotion labels we use to describe our affective state. More specifically we propose a two stage (prediction-outcome) modelling approach. In the first stage an emotion is constructed from the combination of the person's arousal, valence and predictions of the future, while in the second stage we utilize the combination of the person's arousal, valence and evaluation of an outcome. As an example flow can be described as a state of medium-high arousal where one makes a positive prediction about the future, while excitement is a state of positive valence, high arousal and is mostly related with a better than expected outcome. The AV and AT models have already been used in AC applications (Mandryk, 2007), (Karyotis, 2015) thus it would be interesting to explore the performance of this mix-modelling approach in AC systems.

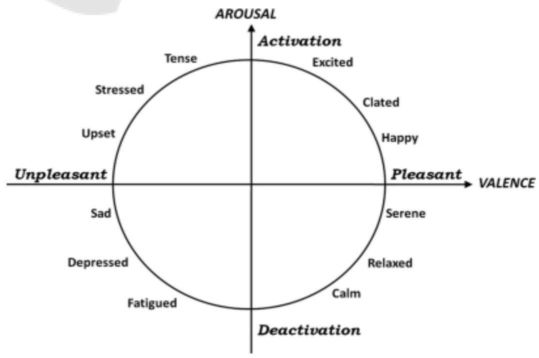

Figure 2: Russell's Affect Grid.

In the following sections we aim to highlight the potential efficacy of this model, and introduce an appropriate AC system's architecture able to utilize our model beyond context constraints. In section 2 the proposed fuzzy rule extraction and adaptation method is presented, aiming to harvest the necessary information in order to create personalized emotion models. Obtained results, using data collected from a previous study, are also included in this section, demonstrating the stability of our method. The proposed AC system architecture is outlined in section 3. In section 4 a personalised learning system utilising the suggested architecture, fuzzy method and affect modelling approach is presented. In section 5 we test the proposed system with the help of a tutorial session on fuzzy logic and we present the corresponding results. In section 6 conclusions and research directions are being discussed.

2 METHODOLOGY

Our proposed fuzzy modelling approach comprises of three stages. Firstly user data is collected using an online survey as described in section 2.1. Then the fuzzy membership functions (MF) are extracted, and the fuzzy rule-bases are being constructed from the data by using the approach outlined in section 2.2. Finally the general rule base extracted is adapted to a specific participant by utilizing the fuzzy adaptation method presented in section 2.3.

2.1 Data Collection

In order to acquire the necessary data a user study was conducted to gather data relating to the construction of emotions from the proposed basic structural elements. The user study comprises of a survey including stories which describe common real life situations and are context specific (i.e. education). During the survey the user is asked to read the scenario and imagine that they are taking part in the story described. Each story consists of two stages. In the first stage, the starting point of the story is described (e.g. "you are attending a mandatory seminar which you predict isn't going to be useful to you"). In the second part of the story, which follows consequently, the ending of the story is presented to the user (e.g. "the seminar proves to be extremely interesting"). In the first stage, the user is asked to provide ratings of their valence, arousal and prediction while in the second stage the user is asked to rate their valence, arousal and evaluation of the experienced outcome. In both stages, after providing the corresponding values, the user rates the degree to which each of the emotional words (flow, excitement, calm, boredom, stress, confusion, frustration and neutral state) fit their affective state in the story. Every variable is rated using sliders and ranges from 0 to 100. Valence ranges from unpleasant (0) to pleasant (100), arousal from deactivated (0) to activated (100), prediction from very negative (0) to very positive (100) and the degree the emotions fit the story from not at all (0) to perfectly (100). As a result our data samples have 3 inputs and 8 outputs. The inputs for the first stage are valence, arousal and prediction, and those for the second stage are valence, arousal and outcome. The outputs in both stages are values of the eight emotions.

2.2 Fuzzy MFs and Fuzzy Rule Base Extraction

In order to extract the necessary MFs from the data, it is essential that we originally define the number of fuzzy sets we require, in order to cover the input-output space. Subsequently we utilize the FCM algorithm and compute the same number of fuzzy sets' centers. Finally we define the corresponding fuzzy set to have triangular MFs with degree of membership equal to one, at the previously computed by the FCM center. The support is the space defined between the projections of the previous center and the next center on the horizontal axis. Figure 3 displays the extracted fuzzy sets for the prediction element.

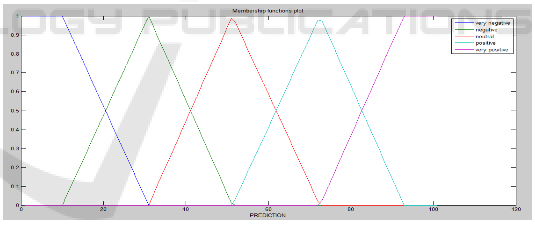

Figure 3: Prediction element's MFs.

The fuzzy rule extraction method is based on the method presented in (Wang, 2005) by Wang. According to this method, initially every data sample is converted to a fuzzy rule. The extracted fuzzy rules are afterwards organized to groups, each group containing the rules with the same if-part. A single rule is then extracted for every group by computing the weighted average of the consequents of the all the rules in the group and by mapping the extracted value to the corresponding output fuzzy set. These fuzzy rules are utilised in our system by two fuzzy classifiers, for stage 1 and 2 respectively, in order to map values of arousal, valence, prediction and outcome to values of the targeted emotions.

2.3 Adaptation

As shown in (Karyotis, 2015) for the AT hypothesis every person uses the basic elements in a personalized way in order for them to select the appropriate emotion label. For this to be accounted in our model we implement a modified version of the Adaptive Online Fuzzy Inference System (AOFIS) (Doctor, 2005) as proposed in (Karyotis, 2015). With this method the user can provide new emotion values if they aren't satisfied with the output of the system, also resulting in changes to the fuzzy rule base. This will allow the system to adjust its general rule base to a specific user, making it more accurate and user-friendly. To achieve this, when the user provides new values, a new training sample is formed, and fed into the system. This new data sample is used by the system to identify the rules that fired and alter the consequent of the rule with the highest activation value. This is accomplished by calculating the optimal position of the output fuzzy set's center of the highest activation value rule, given the contribution of all the other fired rules, and by mapping this value to the corresponding output fuzzy set. Finally we propose that the data samples collected offline from the responses of a specific user at the online survey described before to be presented one by one to the system. This way the system will make all the necessary changes to the fuzzy rule base, thus creating a more personalised system before the user starts using it in a real time setting.

2.4 Results

Since data collection is still ongoing, we used the data collected for (Karyotis, 2015) in order to demonstrate the stability of the system and interpretability of the rules obtained from the fuzzy method discussed above. The results acquired are promising and can be improved and extended upon completion of the data collection and processing phase of the new user study described in the previous section. In (Karyotis, 2015) the data were collected following the method described in section 2.1. However this data do not account for the values of arousal since the survey was aimed at modelling the AT theory. We have inferred some arousal values from the provided emotional values by using the Affective Norms for English Words (ANEW) (Bradley, 2010) database. The values we used for valence correspond to the values of "current state" as used in (Karyotis, 2015), since this variable was used to describe how positive or negative valenced the user was. To follow the aforementioned methodology arousal, valence and prediction values are considered as inputs for the first stage classification systems. While for the second stage classification systems, the inputs are: arousal, valence and outcome values. For both stages the outputs are values of the educational context specific emotions: flow, excitement, calm, boredom, stress, confusion, frustration and the neutral state. For a chosen number of five fuzzy sets for both input and output space we have computed the Normalized Root Mean Square Error (NRMSE) using ten-fold cross validation for stage 1 and stage 2 classifiers of our proposed model (AV-AT) and of the model proposed in (Karyotis, 2015) (AT) . For the adaptive versions (Adaptive AT and Adaptive AV-AT) we considered the values given from a specific participant as changes they have provided during their interaction with the system. The results are shown in table 1.

To demonstrate the ability of the proposed fuzzy approach to produce easily interpretable fuzzy rules, we quote some examples of the rules extracted using this method on the data from (Karyotis, 2015) for excitement and flow.

Table 1: NRMSE of AT and AV-AT models using the proposed fuzzy method.

Emotions	NRMSE							
	Stage1				Stage2			
	AT	AV-AT	Adaptive AT	Adaptive AV-AT	AT	AV-AT	Adaptive AT	Adaptive AV-AT
Flow	0,2559	0,2478	0,1823	0,2098	0.2359	0,2379	0,1724	0,1813
Excitement	0,2432	0,2292	0,1766	0,1770	0.2081	0,2094	0,1654	0,1712
Calm	0,2763	0,2502	0,2175	0,1810	0.2857	0,2573	0,1882	0,1820
Boredom	0,2386	0,2180	0,2057	0,1658	0.2199	0,2102	0,1413	0,1274
Stress	0,2689	0,2284	0,2134	0,2120	0.2473	0,2522	0,1652	0,1591
Confusion	0,2145	0,2063	0,1512	0,1376	0.2331	0,2311	0,1366	0,1375
Frustration	0,2174	0,2175	0,1428	0,1512	0.2001	0,1910	0,1455	0,1862
Neutral	0,2209	0,2215	0,1682	0,1442	0.2064	0,2057	0,1278	0,1186
Overall	0,2420	0,2273	0,1822	0,1723	0.2296	0,2243	0,1554	0,1579

If valence is neutral, and arousal is medium, and prediction is positive, then flow is medium.

If valence is positive, and arousal is high, and outcome is better than expected, then excitement is high.

3 PROPOSED AC ARCHITECTURE

In this section we will outline the architecture of an AC system utilizing the proposed approach. This approach can be applied in different contexts by simply adjusting the output emotions to context specific ones. For example the output emotions of a system installed in a car aiming to aid the driver, could comprise of: panic, fear, frustration, anger, boredom, fatigue (Nasoz, 2010), while for an affective learning system a suitable set of target emotions would be the one used in (Karyotis, 2015). Nevertheless no matter the context of the application, it is necessary to have separate sessions where the start and end points can be clearly defined, so that we can acquire the user's prediction and his evaluation of the experienced outcome. For example in a driving application, a driving session could include a journey, where the driver is able to provide a prediction for the journey ahead when entering the vehicle, and an evaluation of the outcome when leaving the vehicle.

In figure 4 an overview of the proposed architecture can be found. The design encompasses the two-stage classification approach described in section 2. The inputs comprise of the user's arousal, valence, and estimate of prediction for the first stage, while for the second stage the inputs used include: arousal, valence, and evaluation of the outcome. These inputs are fed to the appropriate classifiers in order to be mapped to the context related emotion values. The classification systems also include the adaptation mechanism (described in section 2.3) in order to account for individual differences and make the necessary changes to the fuzzy rule base when the user is not happy with the results and provides new values for the targeted emotions. Valence and arousal have been found to have close relations to different physiological signals. For example, a person's heart rate (HR) (Rainville, 2006) can increase when he is presented with positive stimuli; the galvanic skin response signal (GSR) (Dawson, 2007) is in close relation to their arousal levels and their skin temperature (ST) changes according to their affective state (McFarland, 1985). As a result values of arousal and valence can be acquired either explicitly, by asking the user, or implicitly, by computing estimates of their values using physiological sensors. This can be achieved with the help of non obtrusive wearable devices such as the Autosense, the Empatica E3, or E4 sensors and others.

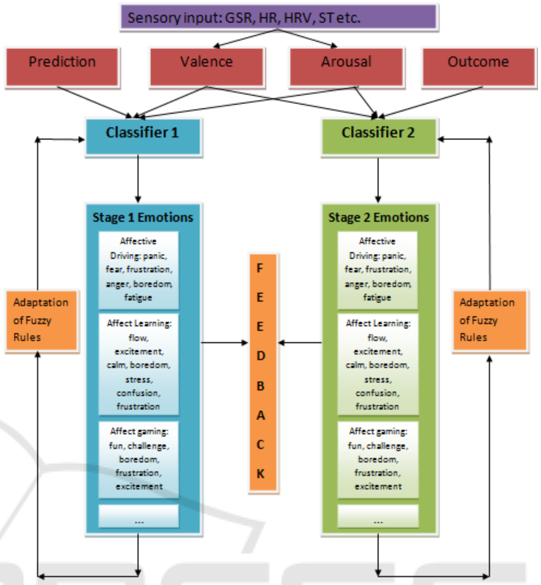

Figure 4: Proposed AC system architecture.

Given the output emotion values and the context of the application, the system delivers the appropriate feedback to the user. More specifically in the context of an affective driving application the system could suggest a break to the driver, or choose a designated favourite radio station on the car's entertainment system, when it detects high levels of frustration. Another example would be affective gaming, where the difficulty level could be adjusted to match the output emotion values. This could be achieved by raising the difficulty level of the game to make the session more challenging, or by decreasing the level to make the game more appealing to novice users. Moreover it would be useful to store the input values of the basic elements along with the system's output values, and the values provided from the user in order to retrain the system, in a future time, when enough data have been accumulated, thus resulting to a rule-base which is more tailored to the user. .

4 PERSONALISED LEARNING SYSTEM

In this section we will present the basic implementation (using Matlab) of a personalized learning system based on the architecture described above. The suggested system aims to aid the student during collaborative, and activity led learning tasks. As mentioned before it is vital for our system to have predefined starting and end points so that the prediction and outcome elements could be provided. In this case the entire learning session would consist of a number of different activities. These activities may include: a lecture, a presentation, a lab exercise, a class game, a discussion etc.

The step by step implementation of the system for a single activity is described below. This process will be repeated for every activity of a specific learning session. At the beginning of the activity the user is explicitly asked to provide a value of his prediction concerning the upcoming activity. At this point of the research, arousal, and valence values are also acquired by explicitly asking the participant. The arousal, valence, and prediction values obtained are used from the system's first stage classifier to provide values for flow, excitement, calm, boredom, stress, confusion, frustration and neutral. The calculated emotional values are presented to the student with the use of bar charts. If a student is not happy with the results they can provide their own values for any of the emotions. These new values will be used by the adaptation mechanism to make the necessary changes to the fuzzy rule base. The system will provide feedback to the student in the form of tips, by taking into account the values of the targeted emotions and the way these emotion influence student's performance. Feedback appears in the form of short motivational quotes or advice ("It appears you have high levels of stress, please try to discuss your concerns with your tutor or take a break"). The average values from every emotion category are also calculated and shown to the tutor, in the form of bar charts. As a result the tutor is able to observe their classes' overall affective state, and thus they are able to adjust their teaching style or classroom conditions, to suit their students' needs.

At the end of the activity the student is asked to provide a value rating of what happened (outcome) in respect to their prediction in the beginning of the activity. Student's valence, arousal and outcome values will be given to the second classifier which would be now responsible for providing the necessary results. The feedback and adaptation mechanism is the same as in the previous stage. It is important to note that the system could be used to observe the student's affective state during activities spanning multiple learning sessions. These student's affective trajectories are stored and can be shown to the student when required, allowing them to reflect on their learning performance. For example in figure 5 we can observe the user's affective trajectory for a session containing 4 activities (8 points).

This AC system has a very low computational burden and can offer its services instantly and without requiring any complex and expensive equipment. A standard laptop or smart phone would be a more than adequate device to run the system along with its adaptive mechanism, which contributes to making the system more user-friendly and accurate.

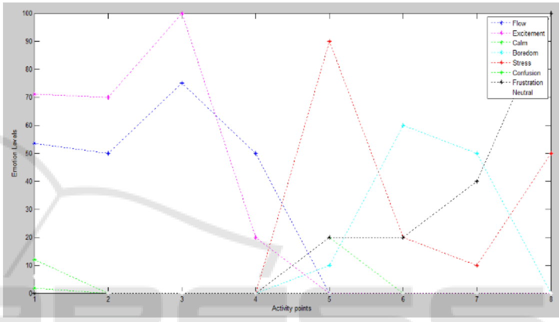

Figure 5: Recorded affective trajectory of a student.

5 SYSTEM EVALUATION

In order to test the performance of the developed system we carried out a practical experimental session, comprising of a tutorial on fuzzy logic, where the participants were utilizing the proposed system. A total of twenty one participants took part in the tutorial. All the participants had completed the online survey in order to provide the necessary data for the construction of a more personalised learning system. The structure of the tutorial was congruent with the limitations of the model and followed an activity led learning based approach. The tutorial comprised of 2 separate sessions which contained 4 activities each. The first session included an introductory lecture on fuzzy logic, a class game designed to introduce the students to the basic fuzzy logic concepts, a discussion on famous quotes concerning the subject and finally a small quiz. The second session included a lecture focused on fuzzy logic as an machine learning approach, example lab exercises using Matlab's fuzzy toolbox, a group project where the students were asked to utilize what they have learned to solve a basic machine learning problem, and finally the students made a short presentation of their work to the class. All the participants used their personal laptops where the system was previously installed. Upon entering the class the participants were divided into groups of three students.

We tested the performance of the system in terms of the emotion recognition accuracy it provided for stage 1 and stage 2 of the emotional model respectively. More specifically we tested the recognition accuracy in terms of the NRMSE error for all emotion categories, and we also calculated the dominant emotion accuracy (DEA) for the AV-AT model in comparison to the accuracy provide it by another affective system if it used the AV model of emotion. As dominant emotion for our system we defined the emotion for which the system provided the highest value. In order to calculate the dominant emotion values for the AV model we initially utilized the Affective Norms for English Words (ANEW) (Bradley, 2010) database in order to define clusters in arousal valence space representing each of the eight emotions (flow, excitement, calm, boredom, stress, confusion, frustration and neutral). The arousal and valence values of those words in the database were used in order to define the cluster centers. Afterwards we utilized the arousal and valence values provided from the participant, and the dominant emotion was defined by calculating the minimum Euclidian distance from each clusters' centers. The results are shown in table 2.

Table 2: NRMSE and DEA results for the tutorial session.

Emotions	NRMSE and DEA for fuzzy Tutorial	
	Stage 1	Stage2
Flow	7.3253	8.8728
Excitement	8.3177	7.1235
Calm	9.3274	8.1050
Boredom	7.2292	9.6106
Stress	10.8370	6.5552
Confusion	6.1300	9.6812
Frustration	7.6439	9.5817
Neutral	5.5270	8.6740
Overall	7.7922	8.5253
AV-AT DEA	88.10%	80.95%
AV DEA	58.93%	60.12%

The results from table 2 show that the performance of the proposed model outperforms the survey results for both stages. This is to be expected due the adaptation process of the system which allowed for a more successful representation of individual differences. Individual differences play a major role in the construction of emotions using the AT theory (Karyotis, 2015) as a result they play a major role in the AV-AT model which is an extension of the AT. The AV-AT emotional model also provides a more efficient emotional modelling approach than the AV model for both stages. This is obvious from the dominant emotion accuracy results. The AT-AV model scored 88.10% for stage 1 and 80.95% for stage2 respectively, while the AV scored around 60% for both stages. These are very logical results since the arousal valence model is not dependant of stages.

6 CONCLUSIONS

In this paper we introduced an emotional modelling approach which combines the Arousal Valence model of emotion, and the Affective Trajectories Hypothesis. We provided a framework in which this model can be utilised in Affective Computing and presented an example of a personalised learning system which uses this architecture. The proposed system is responsible for recognizing and recording the affective state of a student through time, offering in the same time appropriate feedback to aid in the learning process. This system utilizes the suggested novel emotional modelling approach by using an adaptive fuzzy logic mechanism.

Our preliminary results demonstrate the potential of this model, and highlight the applicability of the implemented fuzzy method. By using the data from a previous study we observed that the fuzzy approach used, proves to be stable, promising and in the same time it is able to capture individual differences and preferences through its adaptive part. Additionally the rule base extracted, using this method, contains easily interpretable fuzzy rules. These rules will allow us to visualize how an individual combines the basic elements to choose an emotional label, thus enabling us to create both general and personalised emotional models.

Ongoing work focuses on the collection and processing of data through the online survey described, in order to reveal and model the underlying affect relations. Upon the completion of this process we aim to explore the performance and effectiveness of the proposed emotional model, fuzzy technique and personalized learning system by using the system in a series of practical learning sessions which utilize collaborative and activity led learning tasks. Providing a novel computational methodology to model emotion, will enhance our understanding of the incorporation of emotion in the design of computing systems, resulting in the improvement of services provided by those systems to their users.

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