An intelligent framework for monitoring students Affective Trajectories using adaptive fuzzy systems

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An Intelligent Framework for Monitoring Students Affective Trajectories Using Adaptive Fuzzy Systems

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Abstract—In this paper we investigate the Affective Trajectories Hypothesis in an educational context, and its possible implications on Affective Computing. Using the results from an online survey we try to explore the relationships of the Affective Trajectories basic elements, namely one's current affective state, prediction of the future, and experienced outcomes following this prediction, with a set of education related emotions. The relations of these elements with flow, excitement, calm, boredom, stress, confusion, frustration and neutral linguistic emotional labels are presented and discussed. Their predictive power is evaluated by using these elements as inputs to different classification systems, and observing their performance in mapping different combinations of those elements to specific emotion labels. A data-driven fuzzy approach is utilized in order to linguistically model the underlying relations between the emotions, and the basic elements, by creating easily interpretable fuzzy rule bases. In our research we suggest that the basic elements are combined in a personalized way in order for an individual to choose a specific emotion label to describe his affective state. For this reason a fuzzy adaptive approach is also implemented, in order to demonstrate the importance of individual differences in this process, and the benefits of having a personalized system that can perpetuate modelling of emotional trajectories over learning tasks. Finally an overview and a basic implementation of an affective computing system which uses these elements are presented, and future research directions discussed.

Keywords-affective trajectories; emotional modelling; adaptive fuzzy systems; affective learning

I. INTRODUCTION

Emotions are complex psychological states that arise from the response of an individual when they are presented with an internal or external stimulus. Emotions are short-lived episodes which cause changes in many parts of our physiology (voice, facial expressions, heart rate, skin conductivity etc) [17] [5] [27]. Emotions interact and influence almost every cognitive process of the human brain. Therefore they play a major role in decision-making, performance, motivation, learning, communication, perception, and other processes that affect human life [8] [18] [6] [13] [4] [17] [7].

The task of understanding and classifying emotions has been a subject of debate among researchers, since the early days of psychology. At that time the dominant view was that emotions could be classified into discrete basic emotions. In the 1970s Paul Ekman identified, through cross cultural facial expressions experiments, six basic emotions (anger, disgust, fear, happiness, sadness and surprise) [17]. Another attempt to classify emotions was conducted by Robert Plutchik who identified eight primary emotions (joy, trust, fear, surprise, sadness, anticipation and disgust). Each of these primary emotions has its opposite, and they can be combined to create more complex affective experiences [23]. A newer approach to understanding emotion is psychological constructivism. Constructivism suggests that emotions emerge from the combination of more basic elements such as arousal and valence [24]. However the nature and number of these elements is still being explored [12].

A. Emotion and Affective Trajectories

A different approach in emotion modelling and the basis for the Affective Trajectories (AT) hypothesis is the Iterative Reprocessing Model (IR model) (see Fig. 1). According to this model when environmental or internal changes are presented, a person processes the new information and reaches a new state. Through repeating iterative cycles, the incoming information are processed and used to create more detailed evaluations of information, and complex states such as affect arise [12]. These new more detailed evaluative states are formed dynamically through neural loops which happen constantly, multiple times per second. When we are presented with new information, at any point of time, we process this by making comparisons with the information already possessed and predictions concerning what is about to follow

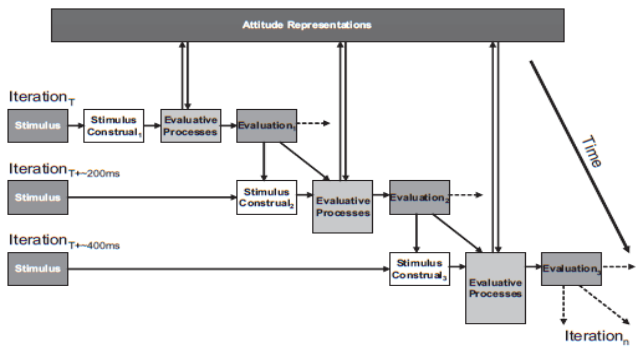

Figure 1. IR Model.

in the future. As a result a current affective state is constructed. As in [20] "Emotion categories depict a way to label and differentiate the various affective trajectories we experience as we move continuously through time".

Based on the ideas of the IR model, and motivated by the need to explain and understand the shifts in affect that got a person to a certain affective state, the AT hypothesis states that emotion arises partly from the interaction of the evaluations of one's current state, predictions of the future, and the outcomes that one experiences after these predictions [11]. These processes interact, and combine with each other to create an emotional experience [20]. The AT theory has been evaluated based on results from experimental sessions which showed that individuals were able to distinguish and differentiate between emotion words using different combinations of simple cues of an affective trajectory through time (current state, prediction and outcome) [20]. It was shown that different emotions relate to different aspects of an affective trajectory, and certain emotional labels can emerge from these various combinations of current state, prediction and outcome. For example fear is related mainly with the prediction aspect, while anger is reported when a combination of a positive prediction and a negative outcome is presented. However there are limitations in these studies since the experiments where generic and not related to a certain real context or specific task.

B. Affect and Learning

Emotion play a vital role in the learning process as it does in almost every aspect of human life. Emotion is closely related to the levels of motivation and engagement of the learner. The performance of a student and the produced learning outcomes are greatly affected by the student's motivation and involvement during the educational procedure. Therefore the emotional state of the student should be taken into account when designing models and systems to collaborate and improve the learning process.

In [25] a connection between the goals and emotions of an individual was demonstrated. When novel information is presented creating a mismatch with already existing schemas, arousal in the Autonomous Nervous System (ANS) is produced. During this phase of ANS activation and cognitive processing, an emotional episode occurs [21]. Consequently we can conclude that learning takes place when an emotional episode is unfolding. The close relation between the affective state of an individual and learning can also be demonstrated by the famous Yerkes-Dodson Law, presented by the psychologists Robert M. Yerkes and John Dillingham Dodson in 1908 [30]. According to this law, performance in mental tasks is almost a linear function of arousal levels for simple tasks, and a non-monotonic function (u-shaped curve) for difficult tasks. Learning can be considered as a complex and difficult mental task.

The six basic emotions identified by Paul Ekman are not known to play a significant role to the learning process. Other emotions are identified and used for this purpose. Amongst these is confusion, where research has shown that it is an indicator of cognitive disequilibrium which correlates positively with the learning procedure [9]. Another emotional state that has been used in learning conditions is flow. Flow is the state where the student is highly involved and interested in the educational tasks, and as shown this has a positive relation with learning [10]. Additionally Craig has also identified emotional states which have negative impact in the learning process, such as boredom and frustration [9].

C. Affective Computing and Fuzzy Logic

In our research we aim to develop an affective system that utilizes the AT hypothesis in order to facilitate the educational process. A complete Affective Computing (AC) system should comprise of basic elements responsible for recognizing, modelling and affecting user's emotion, as proposed by Wu et al. [29] and shown in Fig. 2.

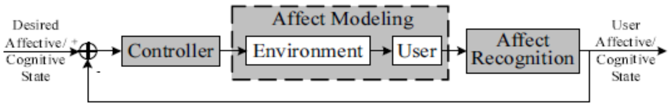

Figure 2. Affective Loop.

This is the basic architecture that we will use for our system. The affect modelling approach used in our system relies on adaptive rule based fuzzy systems. As pointed out in [28] fuzzy logic systems are very efficient in dealing with the uncertainties concerning emotions. Emotions can include both intrapersonal and interpersonal uncertainty. Intrapersonal uncertainty refers to the uncertainty a person has about an emotion at different times and scenarios whereas interpersonal uncertainty can be due to different individuals having different perceptions and expressions of the same emotion [28]. Recently Kazemzadeh et al. has proposed two models based on interval type-2 fuzzy sets to model the meaning of emotional words, and used the extracted models to translate between emotional vocabularies [19]. In an educational context, fuzzy logic systems have been widely used to model students' behaviour and aid in the educational process [16] [1]. In [1] Almohammadi et al.'s presents a fuzzy logic system that can learn and adapt to the needs and learning style of the student. Their system utilizes visual information to automatically calculate the engagement of the student in the learning task.

In the following sections we will aim to demonstrate the usefulness of using the Affective Trajectories Hypothesis in Affective Computing, and present a framework in order to utilize this theory in a complete affective computing system. Initially in section II we will present the results from a user study conducted in order to reveal the correlations which exist between a set of eight education related emotions and the basic AT elements. This will aim to highlight that the AT theory can be utilized under a specific context, and demonstrate how specific emotions are related with specific elements of the AT theory. In section III we will describe our system's proposed data driven fuzzy rule extraction and adaptation approach. The validity and classification performance of our approach will be evaluated against a selection of existing machine learning methods in section IV. The complete mechanism of the proposed AC system will be presented in section V. Finally in section VI the conclusions and future research will be discussed.

II. User Study

In order to achieve our goals, an online user study was conducted investigating the relationships within a set of eight emotions related to education and the AT elements. The eight chosen emotions were: flow, excitement, calm, boredom, stress, confusion, frustration, and the neutral state. For the experiment, we used an online survey tool called QuestionPro. Prior to commencing the survey, participants were asked to provide general information concerning their age, gender, nationality, and educational level. Ninety-five participants completed the survey from which six were excluded due to very poor responses.

During the main experimental session participants were presented with different scenarios describing common situations based in an education setting (e.g. taking a test, attending a seminar etc.), and were asked to picture themselves as taking part in the scenario. The scenarios were divided into two stages which were presented sequentially to the user. In the first stage, the beginning of the story is described, where the valence of their current state (e.g. '*you enter the class feeling happy*') and the prediction (e.g. '*you predict you are going to score well on an upcoming test*') are specified. In the second stage, the participants were presented with the outcome of the story, which was either 'better', 'worse' or 'as they had predicted in the first part' (e.g. '*unfortunately the test was far more difficult from what you expected and the results are really bad*'). In both stages the participants were asked to use sliders provided to rate their current state, prediction, and outcome on a scale of 0 to 100. After scoring on these basic elements in each stage, the participants were asked to choose from the list of 8 emotions, and indicate the degree to which each of the emotional words in the list described their affective state in that stage of the scenario. This was again based on selecting a sliding scale of 0 to 100 that indicated the relevance of the emotional word in describing the perceived affective state.

In accordance with previous work carried out by Kirkland and Cunningham [20], we used 18 separate stories to represent all the 18 possible combinations of the basic elements (positive/negative current state, positive/negative/ neutral prediction, and a better/worse/as expected outcome). Every scenario accounts for a different combination of these elements and was presented to the user in a random order. The scenarios were designed to fit in an educational context so that emotions related to education can be induced. However we tried to minimize the effect which personal experience may have caused to labelling the results by not referring to specific scenarios or subjects that might bias the results. We also provided the participants with the freedom to choose and rate as many of the emotions from the list as they wished, since one emotion category may not be sufficient to describe one's complex affective state.

In order to assess the relations between the aforementioned emotions, and the basic elements of an AT, a Pearson's correlation coefficient was computed. The results of this analysis revealed that every emotion category had significant correlations with the basic elements of the AT theory. As an example the values of Pearson's coefficient for excitement are 0.585 for current state, 0.609 for prediction, and 0.664 for the outcome, representing a strong relation between the levels of excitement and all of the AT elements.

Aiming to provide a better visual comprehension of these relations, we also transformed our original scale variables to categorical variables in order to demonstrate that specific emotions relate more strongly with specific aspects of the trajectory. To perform the transformation we defined three distinct categories for our three basic elements (current state, prediction, and outcome). Our cut points were at 33.3% and 66.6% of the provided values for each element, and the corresponding categories were labelled as 'negative', 'neutral, and 'positive' respectively. The 8 emotions used in our research were: flow, excitement, calm, boredom, stress, confusion, frustration, and the neutral state, where we defined two categories for each: 'feeling' or 'not feeling'.

To illustrate this transformed view of data we present in Fig. 3 the number of paritcipants reporting a specific emotion in the first and the second stage of the survey. We can observe that frustration and confusion are more outcome related emotions, whereas stress, flow, and boredom are more related to the combination of current state and prediction. We can further show how a specific emotion was perceived over the different scenarios (combinations of basic elements) presented in the survey. For example in the results obtained for flow, as shown in Fig. 4. Examining flow we observed that it was mostly related with the prediction element since

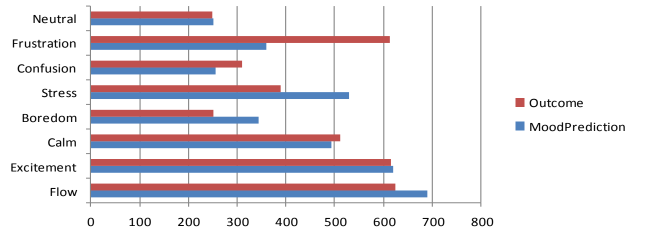

Figure 3. Number of participants reporting an emotion in the first and the second stage of the survey.

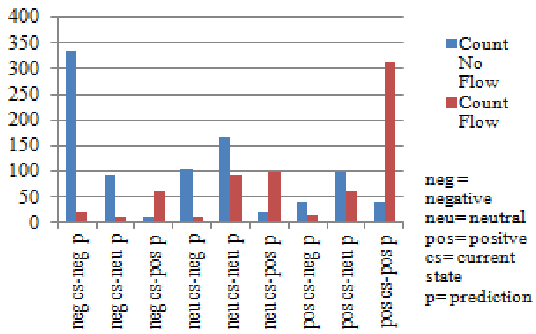

Figure 4. Number of participants who reported flow.

there were a higher number of participants who reported flow in combination with a positive prediction, even when a neutral or negative current state was experienced. This suggests that flow is mostly influenced by one's expectations.

III. FUZZY MODELLING

The strong correlations existing between the AT elements and the emotions under investigation indicate the need for a reliable system that uses the basic elements, to demonstrate clearly these underlying affect relationships. It is also important that even if some general model can be extracted, demonstrating some trends from a larger population of participants, individual differences are considered and the model is flexible in accounting for these. The way an individual perceives an emotional label or the degree, to which they experience a specific emotion, is highly personalized. Every individual may use the basic elements of the AT hypothesis as basic structural elements, but they may combine them in a personalized way in order to choose a specific emotional label to describe their affective state. In order to take this into account the proposed system should have the ability to make these changes to an initially learnt model. To achieve this we have implemented a data driven adaptive fuzzy logic approach which is presented in the following section. Fuzzy rules are extracted from data based on an enhanced version of the Mendel Wang method [26] and the online adaptation part of the system is a modified version of the Adaptive Online Fuzzy Inference System (AOFIS) as proposed in [15].

A. *Fuzzy Rule Extraction.*

Our proposed technique for determining values of the targeted emotions given a user's current state, prediction and outcome comprises of the following steps: collecting user data, extracting the Membership Functions (MFs), and extraction of the fuzzy rule-bases corresponding to each of the two stages of the scenarios presented in the online survey. Firstly we acquire the necessary data as provided from the participants using the online survey. Therefore in our dataset every training sample (s) is in the form of $(x^{(s)}; y^{(s)})$ $s = 1, \ldots . N$ where $N = 1602$ since we had 89 participants providing answers for the 18 scenarios used in our user study. The output variables $y = (y_1, \ldots, y_m)$ are the values for each of the output emotions, and $x = (x_1, \ldots, x_n)$ are the inputs. The inputs for the first stage are current state and prediction, and those for the second stage are current state, prediction and outcome.

After capturing the data the FCM fuzzy clustering algorithm [3] is used to calculate a predefined number of fuzzy sets' in the form of triangular MFs. Every triangular MF has a membership of unity at the corresponding centre which was calculated from the FCM algorithm and its support is defined as the space between the previous and next centres points as shown for example in Fig. 5 for the prediction element. This is a simple approach for constructing a model where the level of information can be quantified as the number of fuzzy sets used to depict the underlying knowledge.

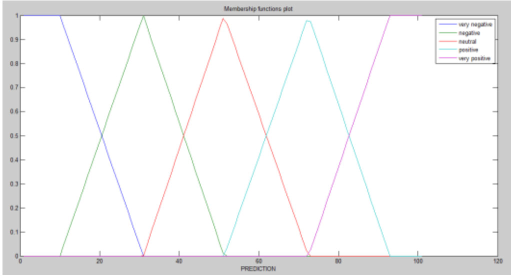

Figure 5. Membership functions for prediction.

After this process the input and output space is divided into the predefined number of fuzzy sets $(fnis$ and $fnos)$. Let F_c^p be the corresponding fuzzy set for the input c and G_d^q be the corresponding fuzzy set for the output d where $p = 1, \ldots, fnis$ and q$= 1, \ldots, fnos$. Our goal is to extract rules from the data in the following form.

If x_1 is F_1^p and... x_n is F_n^p then y_1 is $G_1^q$and...and y_m is G_m^q (1)

This process will be described for one output but can be easily extended to include multiple outputs.

For every training data pair $(x^{(s)}; y^{(s)})$ we compute the membership values $\mu_{F_c^p}(x_c^{(s)})$ for every input $c = 1, \ldots n$ which are mapped to all corresponding input fuzzy sets $p = 1, \ldots, fnis$. We then find $\acute{p}$ such that

$$\mu_{F_c^{\acute{p}}}(x_c^{(s)}) \geq \mu_{F_c^p}(x_c^{(s)}) \tag{2}$$

for $p = 1, \ldots, fnis$. The following rule is then generated from the sample$(x^{(s)}; y^{(s)})$:

If x_1 is $F_1^{\acute{p}}$ and ... x_n is $F_n^{\acute{p}}$ then y is centered at $y^{(s)}$. (3)

The weight $w^{(s)}$ of the rule is also calculated as:

$$w^{(s)} = \prod_{c=1}^{n} \mu_{F_c^{\acute{p}}}(x_c^{(s)}) \tag{4}$$

At this point we will have as many rules as samples ($N = 1602$). The rules are then divided into W groups. Every group contains rules which have the same antecedent part. The number of rules in the group will be the same with the number of the training samples which belong to that group. Let group g have N_g data pairs (s_u^g) $u = 1, \ldots, N_g$ and N_g rules in the form:

If x_1 is $F_1^{(p^g)}$ and ... x_n is $F_n^{(p^g)}$ then y is centered at $y^{(s_u^g)}$. (5)

The weighted average of the rules in the group is calculated as:

$$av^{(g)} = \frac{\sum_{u=1}^{Ng} y^{(s_u^g)} w^{(s_u^g)}}{\sum_{u=1}^{Ng} w^{(s_u^g)}} \tag{6}$$

$av^{(g)}$ is then mapped to all corresponding output fuzzy sets G^q $q = 1, \ldots fnos$ where we find $\acute{q}$ such that

$$\mu_{G^{\dot{q}}}(\, av^{(g)}) \geq \, \mu_{G^{q}}(\, av^{(g)}) \quad (7)$$

All the rules in the group are then combined to a single unique rule:

If x_1 is F_1^g and ... x_n is F_n^g then y is G^g. (8)

where G^g is the fuzzy set chosen in the previous step. The maximum number of rules generated would be $fnis^n$. Because of the small number of inputs (2 for the first stage, and 3 for the second) when a small number of fuzzy sets is selected to cover input space we can have a rule generated from the data to represent every possible input combination. The final rule bases containing M rules are extracted to define the fuzzy classifiers for stage 1 and 2 which will use product inference, singleton fuzzification and centre average defuzzification to map the input $x = (x_1, \ldots, x_n)$ to the output y as follows:

$$y = \frac{\sum_{g=1}^{M} y_{center}^{(g)} (\prod_{c=1}^{n} \mu_{G_c^{(g)}}(x_c))}{\sum_{g=1}^{M} (\prod_{c=1}^{n} \mu_{G_c^{(g)}}(x_c))} \quad (9)$$

Where $y_{center}^{(g)}$ is the center of the output fuzzy set G^g of rule(g). The values provided for the targeted emotions can then be used by an AC system in order for appropriate actions / feedback to be decided and presented to the user.

B. Adaptation Method

There is a need for the rule base to be adaptive to reflect individual differences of users emotion perceptions and changes in their affect evaluations and responses that may occur over time. To achieve this we allow the system to modify rules in its rule base when it is presented with new information. In our system the changes only target the rule with the highest activation or firing value. This rule will contribute the most in the result and is the one which most reflects the individual user preferences. So when the user is not happy with the values of the target emotions provided by the system they are able to provide new values for those emotions in the form of a new training sample which will result to changes in the rule base as described below.

Let $(x^{(s)}; y^{(s)})$ be a new training sample presented to the system. We calculate the membership values $\mu_{F_c^p}(x_c^{(s)})$ for every input $c = 1, \ldots n$ and every corresponding fuzzy set $p = 1, \ldots, fnis$. Then the rules whose activation value is > 0 are identified. Let $w^{(g)}$ be the activation value of the gth rule which fired and L the total number of activated rules. The rule $\acute{g}$ with the highest activation value is identified. Then the consequent of the rule $\acute{g}$ is replaced, based on calculating the 'optimal' position of the centre of the output fuzzy set of this rule, by taking into account the contribution of all the remaining L-1 rules that fired, as follows:

$$y_{nc} = \frac{y^{(s)} (\sum_{g=1}^{L} (\prod_{c=1}^{n} \mu_{G_c^{(g)}} (x_c^{(s)}) - \sum_{g=1}^{L-1} y_{center}^{(g)} \left(\prod_{c=1}^{n} \mu_{G_c^{(g)}} (x_c^{(s)}) \right)}{\prod_{c=1}^{n} \mu_{G_c^{(\acute{g})}} (x_c^{(s)})} \quad (10)$$

After y_{nc} is computed we find among the output fuzzy sets $G^q \; q = 1, \ldots fnos$ the $\dot{q}$ set for which:

$$\mu_{G^{\dot{q}}}(\, y_{nc}) \geq \, \mu_{G^{q}}(\, y_{nc}) \quad (11)$$

Finally the consequent of the rule $\acute{g}$ is replaced by $G^{\dot{q}}$. This method is a modification of the rule adaptation approach described in [15].

IV. STATIC AND ADAPTIVE MODEL PERFORMANCE

We tested the performance of the proposed fuzzy AT modelling system and compared it with the performance of different classification systems at mapping the basic elements to values of flow, excitement, calm, boredom, stress, confusion, frustration and the neutral state. We used the captured survey data described in section II. A two stage fuzzy classification approach was adopted to map the interactions of the combinations of basic elements to output emotional labels defining an AT. In stage one, we use as inputs the ratings of current state and prediction of the participant and in stage two, we use as inputs the ratings of current state, prediction and evaluation of the outcome of the participant. In both stages the target variables represented the degree (0-100) to which the participant feels the corresponding labelled emotions. We tested and compared the results of our Fuzzy Method (FM) with those obtained from different machine learning approaches namely: a Linear Classifier, a Regression Tree (RT) a Multilayer Perceptron (MLP), and a Radial Basis Function Network (RBF). For the RBF and MLP a single hidden layer was used, containing ten hidden nodes. The MLP used hidden neurons with sigmoid activation functions, and the RBF used the softmax activation function for all hidden units. For our fuzzy method we choose five triangular fuzzy sets to partition the input and output space so that the rule-base would be easily interpretable.

In order to assess the accuracy of the corresponding classifiers, the Normalized Root Mean Square Error (NRMSE) was calculated using ten-fold cross validation. The results in table 1 suggested that even simple classification systems have reasonable accuracy on mapping different combinations of the basic AT elements, to the rated emotional labels. As we can see in table 1 the fuzzy method had a comparable to marginally better performance for both stages when compared to the other systems. Additionally it provided us with easily interpretable rule bases to help observe the underlying relationships, in contrast to other methods, such as the MLP and the RBF, which can be considered as 'black box' approaches.

We also tested the stability and performance of the adaptive system, using the responses provided by a specific participant in the survey, as desired changes to the pre-trained system's predicted values to modelled input states (based on the training data). Tuning of the system for a new participant could be done both online (during an activity) or through having them complete an offline version of the survey described in section II, and feeding these responses to the

Table 1. Normalized Root Mean Square Error for the static systems.

Emotion	Normalized Root Mean Square Error(NRMSE)									
	Stage 1 Classifier(current state, prediction)					Stage 2 Classifier(current state, prediction, outcome)				
	Linear	MLP	RBF	RT	FM	Linear	MLP	RBF	RT	FM
Flow	0,2684	0,2461	0,2501	0,2701	0,2559	0,2615	0,2428	0,2693	0,2654	0.2359
Excitement	0,2575	0,2355	0,2411	0,2598	0,2432	0,2457	0,2113	0,2606	0,2298	0.2081
Calm	0,2787	0,2738	0,2753	0,2865	0,2763	0,2966	0,2846	0,2858	0,3380	0.2857
Boredom	0,2458	0,2359	0,2390	0,2446	0,2386	0,2240	0,2249	0,2204	0,2760	0.2199
Stress	0,2789	0,2657	0,2702	0,2723	0,2689	0,2657	0,2483	0,2536	0,3156	0.2473
Confusion	0,2170	0,2128	0,2149	0,2212	0,2145	0,2453	0,2363	0,2209	0,2987	0.2331
Frustration	0,2288	0,2133	0,2134	0,2102	0,2174	0,2441	0,2005	0,2680	0,2371	0.2001
Neutral	0,2363	0,2200	0,2243	0,2373	0,2209	0,2566	0,2168	0,2460	0,2386	0.2064
Overall	0,2514	0,2384	0,2410	0,2502	0,2420	0,2549	0,2332	0,2537	0,2749	0.2296

system in order to tailor the generalised rule base modelled from a larger population of participants. In table 2 we show the results in terms of NRMSE for our non-adaptive system (FM) adaptive classifier (AFM) and AOFIS where the rule-bases extracted from the general population are modified based on the responses provided by a specific participant in the survey. All three systems were also tested with different numbers of input-output fuzzy sets. We can observe that the adaptive system proves to be more accurate than the non-adaptive system, and also has better performance than the AOFIS system for a small number of fuzzy sets. Considering the fact that the adaptive part was specifically designed in order to reflect individual preferences, the results suggest that every individual combines the basic AT elements in a way which may follow the general population to a degree, but at the same time deviate in these combinations based on personal preferences.

Table 2. Normalized Root Mean Square Error for the Adaptive Systems.

Number of Fuzzy sets	Overall Accuracy (NRMSE)					
	Stage1			Stage2		
	FM	AFM	AOFIS	FM	AFM	AOFIS
3	0,2529	0,2441	0,2957	0,2468	0,2020	0,2992
5	0,2436	0,2035	0,2472	0,2322	0,1639	0,1877
7	0,2386	0,1803	0,2154	0,2243	0,1543	0,1327

In order to demonstrate the interpretability of the rules obtained, and how they reflect the underlying theory, we present as an example the rules obtained for ‘flow’ from the general population and the corresponding adapted rules extracted by the system for a given participant.

General: *If mood is neutral and prediction is positive then flow is medium*.
Participant: *If mood is neutral and prediction is positive then flow is very high*.
General: *If mood is negative and prediction is positive then flow is medium.*
Participant: *If mood is negative and prediction is positive then flow is medium.*

By looking at the rules for flow shown above we can observe that they are in accordance with the results discussed previously in section II, demonstrating the ability of the system, to linguistically capture the relations existing in our data for both the general population, and a specific participant.

V. PROPOSED SYSTEM

Below we present the proposed implementation of a system aiming to utilize the AT hypothesis in order to recognize students’ affective states, monitor their ATs through time, and provide feedback in order to positively influence their learning. This implementation would require an educational session (lecture, meeting etc.) to be divided into activities (i.e. a short quiz, a student's discussion, a lab exercise, a class game) with specific goals (learning outcomes or objectives) in order to be applied effectively. Hence a collaborative and Problem Based Learning (PBL) [14] [2] provides a well-structured student centred pedagogical framework for implementing our approach.

A basic architecture of the proposed system can be seen in Fig. 6. Inputs of the system are the basic elements of the AT hypothesis. These inputs can be acquired either explicitly or with the use of physiological sensors. Physiological signals such as Skin Temperature (ST), and Heart Rate (HR) extracted from Electrocardiogram (ECG), can be used to provide an estimate of the users current state, since they are related to the valence of the experienced affective state [27] [22]. The backbone of the system are two classifiers based in the fuzzy method described in section III, which are

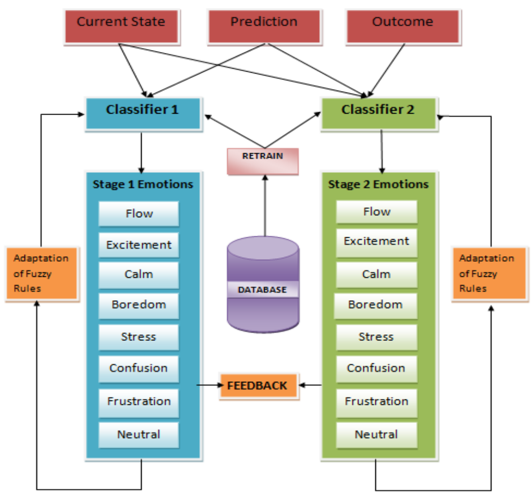

Figure 6. Overview of the proposed affective computing system.

responsible for modelling and recognising the user's affective state. The system also includes an adaptive mechanism (as described in section III.B) able to deliver the necessary changes to the fuzzy rule bases when appropriate. Based on the predicted values of the emotion labels, the system delivers the necessary control actions through its feedback mechanism. The values for the basic elements along with the corresponding targeted emotion values of each AT are stored in a database so that after completing a significant number of sessions, the system could be retrained by using this newly acquired user specific data.

The system would be responsible to monitor the AT of the student through a number of N activities A_i where i = 1 to N. These activities could span over a single or multiple learning sessions and each activity would be defined by a start and end point denoted as A_i^{str} and A_i^{end} respectively. As a preliminary step of this process the participant is asked to take an offline version of the survey. This will allow the system, which is originally trained on a population of users to shift towards a more tailored fuzzy rule-base. This will be achieved by adapting the generic model using the participant's answers. A step to step implementation of the system concerning a single activity A_v is outlined below. At A_v^{str} the student is asked explicitly for their prediction:

[In the next part of the lecture we are going to have a short quiz on Fuzzy Logic. How well do you believe you are going to do?]

Their prediction along with their current state will be given to the first classifier in order to predict the values for each of the targeted emotions. These values are presented to the user in the form of bar charts as shown in Fig. 7, where they can adjust the influence of each emotion resulting in the necessary changes to the rule base of the first classifier. Given the provided output values of the eight emotions, and by taking into account their effect on the student's performance, the system delivers appropriate feedback to the student. This could be given in the form of tips concerning the detected affective states. For example if high levels of stress are predicted the system may deliver suggestions to have a break or discuss their issue with members of their group or the tutor. The tutor might also be notified that the student is in need of assistance or may be having some personal issues. At the same time the overall affective states of the class (average values for every emotion category) are

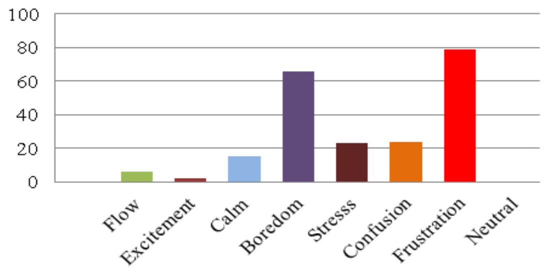

Figure 7. Overall affective state of the class as presented to the lecturer.

also calculated and presented to the lecturer (see Fig. 7) to allow them reflect on their performance and make the necessary changes in their teaching style, or classroom management.

At A_v^{end} the student is asked to provide their evaluation of the activity's outcome in respect to their previous prediction.

[Your prediction was that you were going to score well. How would you rate what happened in respect to your prediction?]

The activity's current state, prediction and outcome will be used by the stage 2 classifier to provide values for the target emotions. Again the user has the option to provide their values of the emotions resulting this time in changes in the rule base of the stage 2 classifier. As before, feedback is given to the student and the lecturer and the process is repeated for every subsequent activity.

The stored values of every emotion are available at any point in time to be presented to the user as feedback so they can reflect on their performance. As an example for 7 activities spanning across 2 sessions, flow, boredom and frustration levels of the student will be recorded and presented back to them as shown in Fig. 8. However we must emphasize that the recorded affective states reflect those perceived by the user at the point at which they were captured by the system. Consequently we do not claim that they reflect over the duration of the learning task, but rather provide a picture of the changing emotional states of the user with respect to the learning tasks.

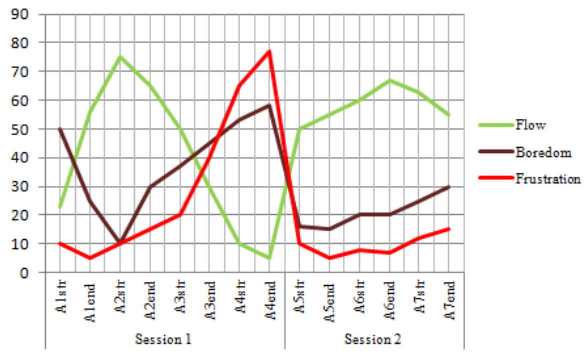

Figure 8. Affective Trajectories of a student.

The proposed system will not require any specialized or complex equipment in order to deliver its services due to its low computational cost. It would typically use a smart phone or tablet to run the adaptive recognition mechanism and present the suggested feedback to the user. The system's ability to adapt to a specific user offering them the opportunity to make changes to its prediction about their affective states, makes it both user friendly and able to achieve higher recognition accuracy. The feedback mechanism is also a crucial part of any affective computing system. Providing appropriate affect informed feedback to the student ehnance the beneficial power of feedback and reflection to aid the educational process both in terms of helping the student to improve their performance and enableing the tutor to better adjust content to suit the learning needs of their class.

VI. CONCLUSION

In this paper we investigated the importance of using the AT hypothesis in affective computing, and we have presented a system which utilizes this theory through an adaptive fuzzy logic approach, in order to monitor a student's AT, and facilitate the educational process.

Our study has shown that participants in context of a specific scenario such as education choose specific emotional labels using only the basic elements (current state, prediction and outcome) of their affective trajectory through time. We observed significant correlations with these basic elements and associated context dependent emotional labels that were selected and rated by participants.

The proposed adaptive fuzzy approach can enable the successful modelling of observed relationships between the basic elements and emotional labels. The accuracy of the fuzzy system was either comparable or better in comparison to other well-known machine learning approaches. The approach provided a means to create both generic and personalized AT models. This was due to the adaptation capability of the fuzzy rules to incorporate individual preferences into the learnt model. The interpretable nature of fuzzy rules also enables them to easily visualize an individual's ATs in different real world settings for realising closed loop affective computing systems.

The basic AT elements seem to provide a reasonable representation of our affective state. However it is in our intentions to use this modelling approach in collaboration with the arousal-valence model in order to provide a more complete monitoring of ATs in context of real educational scenarios. Future work will also consider utilizing the proposed system to monitor groups of students in collaborative learning tasks. Having multiple users would result in complexities related to the interference and interactions of their ATs, posing new challenges in modelling these dynamic affect systems.

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