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Detecting Academic Emotions from Learners' Skin Conductance and Heart Rate: A Data-driven Approach using Fuzzy Logic

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Abstract: In this feasibility study, we have designed and conducted an Emotional Picture Experiment, which is based on International Affective Picture System (IAPS). We presented 96 affective visual stimuli to 27 participants and asked them to rate their emotions in terms of valence and arousal, while recording their EDA and ECG sensor data. On the recorded sensor data, we adapted and applied a fuzzy logic model which was presented in 2007 by [MA07]. To optimize this fuzzy logic approach in terms of finding better membership functions and rule sets, we used a genetic algorithm. The results show closeness of valence and arousal values derived from sensor data to ratings of the affective pictures provided by IAPS, which means that our fuzzy logic system could be used to assess and detect emotions in a learning context.

Keywords: academic emotions; arousal; valence; affective pictures; fuzzy logic; genetic algorithm; learning indicators

1 Introduction

Learners experience positive emotional states (happiness, satisfaction) as well as negative emotional states (boredom, frustration) [Gr16]. In spite of broad previous studies in emotion, research of emotion in a learning context is still in a beginning stage. In our study, we aim to investigate the relationship between sensor data and academic emotional states. Firstly, we adopted the two-dimensional emotion model to apply academic emotion conceptually [Yu17]. Secondly, we designed and conducted an emotional picture experiment based on the International Affective Picture System (IAPS) while collecting physiological sensor data using ECG (electrocardiogram) and EDA (electrodermal activity) sensors. Thirdly, we applied a fuzzy logic approach which was used in Mandryk and Atkins [MA07] to accumulated sensor data. Based on first results, we optimized our approach using genetic optimization. We finalized the paper by reflecting on our experiment data analysis and discuss future work on emotional assessment to support learners in form of a context-aware learning-support system.

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2 Emotional Picture Experiment (EPE)

2.1 Academic Emotions and Sensor Data

Learners encounter the changes between positive and negative emotional states with varying degree and the negative condition such as boredom undermines learning achievement and experience [Gr16]. In fact, learners' knowledge attainment is linked to emotions that learners face in an academic situation [IYF10]. Academic emotions which are defined as emotions that are relevant in a learning context [Wo09] are highly relevant to successful learning. During learning, learners experience various emotions, yet experiencing the whole spectrum of emotion during learning is not common. For example, boredom, frustration, excitement and satisfaction may be emotions that learners experience whereas disgust, fear or sadness are not considered frequently in a learning context. To model emotion, one study utilized Ekman's facial expression data to investigate emotions occurred during a learning situation [Ar09] and others took a two-dimensional model of emotion [LB07a] [Wu94]. Our classification of academic emotion [YFP17] relates to a two-dimension model of emotion which consists of arousal and valence. For instance, high valence and high arousal (HVHA) refers to excited and joyful state and high valence and low arousal (HVLA) relates to concentrated and satisfied state. Low valence and high arousal (LVHA) indicate frustrated and angry state and lastly, low valence and low arousal (LVLA) indicate bored and tired state.

Methods such as human observation, self-report and hardware sensors with mathematical classification have been used [Dr08] to detect emotions. Regarding on sensor data, EDA, respiratory rate, EMG (electromyogram) and ECG were widely used to investigate the relation between physiological response and emotion [Kr10] [Co02]. Derived ECG values such as heart rate (HR), heart rate variability (HRV) and heart rate acceleration were researched to relate with emotion. For example, heart rate variability was found to be linked with two sides of emotions (positive to negative) [Re15] and heart rate acceleration has positive relation to intense negative emotion (fear) [VCL86]. Additionally, EDA was found to be linked to emotional intensity (arousal level) [LO86] [CM15]. Based on the previous work relating two-dimensional emotion model with academic emotion [Yu17], we have selected the visual stimulants for emotion study to explore physiological signals during emotional picture viewing.

2.2 International Affective Picture System (IAPS)

The International Affective Picture System (IAPS) contains 1182 standardized emotional stimuli that are based on a two dimensional emotional model including valence and arousal [LB07b]. Valence indicates a range of positive to negative nature of affect whereas arousal represents the degree of affect [Fr86]. For instance, joy and anger are classified as similar degree in arousal (high), one with positive valence (joy) and the other with negative valence (anger). On the other hand, both satisfied and joy state lie on same positive valence axis, although the arousal level of both states is different. To assign specific weight on each picture, the initial IAPS experiment includes a graphical representation of valence and arousal (Self-Assessment Manikin).

Based on the large samples of people with a broad range of age group and gender, each picture is provided with mean value of valence and arousal with respective standard deviation. This large library of pictorial stimuli serves as controlled independent variables to explore emotional responses. Physiological responses such as facial EMG, skin conductance, heart rate, brainwave, blood oxygen level, respiratory changes and other investigations have been used in IAPS picture experiment to find relationship between physiological responses and picture ratings [La95]. In fact, skin conductance has been found to have close relation with arousal level and cardiac acceleration/deceleration has been found to be responsive while viewing different pictures with degrees of valence [VCL86] [Zu13].

2.3 EPE Design and Results

For this study, we have focused on investigating emotion therefore, we have adopted ECG and EDA sensors to record participant's physiological signals. For the experiment, we have adapted the IAPS experiment setting to stimulate four types of academic emotions based on a two-dimensional emotion model.

IAPS reference ratings of valence and arousal were used to assign appropriate pictures to respective emotions. To better induce specific emotions, out of 1182 IAPS pictures, 96 pictures were selected and each category (HVHA, HVLA, LVHA or LVLA) consisted of 24 pictures. As for the picture selection process, we have considered the gender effect, ethics, degree of ratings and their standard deviation. To minimize the gender effect on the experiment, pictures that have no significant statistical difference in ratings (valence and arousal) between genders were selected using independent t-test. The mean valence rating difference between female and male was less than 1. The mean arousal rating difference between female and male was less than 0.8. This resulted in 735 pictures. To select pictures that are targeted to the specific category, pictures containing explicit violence and sexually explicit were excluded and rating value higher than 6 and rating value less than 4 were used respectively. Furthermore, the range of standard deviation was kept as low as possible (less than 2.5). The 96 pictures selected for EPE were displayed in a random order (preparation 5 second - picture view 6 second - rating 10 second). Some pictures depicted explicit content which required consent from the participants. Additionally, the consent form included the description of the experiment and the collection of physiological data collection for research purpose. When the experiment was finished, we showed a short video to reestablish the participants' emotional state.

2.4 EPE Sensor Data for Emotion Detection

During our EPE, we recorded the participants' EDA and ECG sensor data with the Bitalino (R)evolution Plugged Kit[5] which comes with a 10 Bit analog-to-digital converter (ADC). Each participant had 3-lead pre-gelled electrodes on their chest for ECG signal detection and 2-lead pre-gelled electrodes on the intermediate phalanges of the index and middle finger of the non-dominant hand (mostly left hand) for EDA signal. Communication with the sensor device was accomplished by Bluetooth. The signals were recorded with a sampling rate of 1000 Hz using the manufacturer's software OpenSignals for persistence and visual verification. Raw ADC values provided by Bitalino sensors were transferred to millivolts (ECG) and microsiemens (EDA). From the EDA signal, a slow changing component (SCL, Skin Conductance Level) and a fast changing component (SCR, Skin Conductance Response) can be derived. While SCL reflects overall changes in sympathetic arousal, SCR occurs as an immediate consequence of stimuli [Ch81]. Regarding emotions, a depressed state can be associated with low SCLs together with reduced nonspecific SCRs [Ch81].

Besides HR (Heart Rate), HRV (Heart Rate Variablity) is used as an indicator for the state of a person's autonomic nervous system [Ca96] and it has been identified as a possible indicator for emotions [Gr15]. HRV can be analyzed with respect to their frequency or time domains. For HRV analysis in the time domain, it is claimed that only measurements obtained from recordings of the same length (short or long) should be compared [Ca96]. There are also reports on ultra short time analysis (less than 5 minute) such as the square root of the mean squared difference (RMSSD) for which a 10 second window shows significant correlation to the respective 5 minute recording [Th03]. Frequency analysis of HRV regards the balance between sympathetic and vagal activity [HG17]. While HR was computed from the ECG signal using the Hamilton method [Ha02], we derived SDNN (standard deviation of RR intervals) and SD2 (standard deviation of RR interval differences) over a given window of 16 seconds (viewing and rating), referring to [Pe17] where SDNN/SD2 windows of 30 seconds may be used for stress detection.

3 Deriving Emotions from Sensor Data via Fuzzy Logic

To assess learners' emotions from sensor data, we have to deal with partial, imprecise knowledge and imprecise data (Setz et al. claim that "EDA peak height and the instantaneous peak rate carry information about the stress level of a person" [Se10], and a valence of 6 in Lang's emotional model [La95] describes a rather happy, content person). In a human-like manner, fuzzy models allow expert knowledge as sets of simple rules (e.g. IF eda IS high THEN arousal IS high). Fuzzy membership functions allow for partial membership of input and output variables around the boundary of classes (e.g. low, midlow, midhigh, high).

We started out with a fuzzy logic model for assessing emotions as presented by Mandryk and Atkins [MA07]. In a gaming environment, they used EDA and HR signals for arousal, and for valence HR and EMG signals, the latter indicating smiling or frowning activi-

[5] http://bitalino.com.en

ties. In our experiment, we are restricted to EDA and ECG signals, so we opted for using SDNN and SD2 to derive valence values. Additionally, we used a genetic algorithm to improve the arousal model, and to find a viable model for valence. This goes back to work by Koza in 1990 [Ko90]. Even though the first boundaries are based on uncertainties, the heuristic approach offers usable results at relatively low computational costs. Additionally, as the emotional state is imprecise and difficult to be expressed numerically, some false classifications can be tolerated easily [Za96].

3.1 Fuzzy Logic to Assess Emotions

Through fuzzy logic, we can assess valence and arousal values, which serve as indicators for emotions. Fuzzy logic provides a way to approximate and quantify granular input expressed as linguistic variables [Za94]. In our fuzzy model, input variables consist of EDA, HR, SD2 and SDNN, whereas arousal and valence serve as output variables. Membership functions transform the membership of a specific element into a percentage membership in the set of values. The fuzzy logic system weights each input signal, defines overlap between the levels of input, and determines an output response. A set of IF/THEN rules use the input membership values as weighting factors to determine their influence on the fuzzy solution sets. Once the functions are inferred, scaled, and combined, they are defuzzified into a solution variable (scalar output) [Co92].

To assess arousal, we started with a fuzzy logic system as proposed by [MA07], with EDA and HR as input variables, triangular membership functions and with a set of eight rules. In the case of valence, there is no clear evidence in the literature how input variables which can be derived from the ECG signal (e.g. HR or SDNN) correlate with valence, or any form of emotion [Re15]. SD2 and SDNN input variables seemed to fit best to our study design. Therefore, we started out with a fuzzy logic model with input variables SD2 and SDNN, together with a random ruleset.

3.2 Improving the Fuzzy Model via Genetic Optimization

Genetic optimization is a form of probabilistic reasoning which can be employed in combination with fuzzy logic, which provides advantages over other methods of optimization [Za96]. Both membership functions and rulesets can be parameters of genetic optimization. The fitness function used in our optimization is “closeness” of the obtained values for each picture to IAPS ratings. This can be expressed as the mean squared error (MSE) over all EPE pictures, which in the case of valence is defined by

$$MSE = \frac{1}{N} \sum_{i,j} (v_{i,j} - v_i')^2$$

where $v_{i,j}$ is the valence value derived for picture i and participant j, and v_i' is the IAPS rating for picture i.

As a first step, the genetic algorithm generates an initial population. In each optimization step, new individuals are created using cross-over and mutation, and added to the population. The size of the population remains stable, so after each step, only the fittest individuals survive. The uniform crossover and mutation rates (20 % and 1% respectively) were kept low, conforming to common recommendation [HR07]. The genetic algorithm was configured to terminate when MSE remains constant for 500 iterations, which indicates that no further improvement can be achieved.

For arousal, we took the rules by [MA07], and just optimized membership functions. There are four membership functions for EDA and three for HR, yielding 21 parameters for optimization. In the case of valence assess- ment using input variables SD2 and SDNN, we start with a generic (chaotic) population, including random membership functions and rule sets. Out of a set 32 possible (even contradicting) rules, each individual of the initial population obtains a random subset of these rules. Assuming four triangle-shaped membership functions per input variable, this yields 24 membership function parameters. Together, we acquire 56 parameters for optimization.

3.3 First Results

The arousal inference system optimized against IAPS reference arousal values yielded a best MSE value of 2.39, after a total of 1706 iterations. To verify the result, we repeated the optimization with a modified fitness function, which uses mean arousal values provided by participants in our experiment instead of IAPS reference values. In this case, it took more time for the optimization to terminate (2958 iterations), yielding about the same MSE value for arousal (2.40). While the genetically optimized HR membership function boundaries for both systems were almost identical, significant difference was observed in the shape of the EDA membership functions.

The differences between the two systems is a consequence of the deviation between the IAPS reference values and the participant-provided ratings. Although we expected the participant-provided ratings to reflect the emotional states more accurately, this was not the case, and the system produced from IAPS reference values had a lower MSE than the one produced from participant-provided values. The EDA membership functions varied highly between the two systems as EDA is the attribute that reflects arousal more strongly, as is hence more affected by the change in ratings.

We also optimized the fuzzy model for valence, using both rulesets and membership functions (SDNN, SD2) as parameters. While we could use a “valid” ruleset in the case of arousal, we had to start optimization of the valence model with generic (chaotic) rules for SDNN and SD2. Optimization terminated after 1795 iterations and yielded an MSE of 3.587, which is much worse than MSE for arousal. The final ruleset for valence contained 7 rules.

4 Discussion and Outlook

The work presented in this paper was a feasibility study to relate sensor data (EDA,HR, SD2 and SDNN) to academic emotions. Linguistic terms for recognizing emotions by human judgement can easily be expressed in a fuzzy logic system, which makes it easier to interpret our results as indicators for academic emotions. However, the study focused on exploring the practicality of fuzzy methods to investigate physiological data to indicate academic emotion. Conceptually, we related academic emotion to a two dimensional emotion model, yet a future study should aim at detecting emotions in a learning-relevant context.

Relating sensor data to emotions is a challenging task. Especially for valence it is difficult to relate features such as HRV (time or frequency domain) to values which exactly indicate emotions. In this case, genetic optimization proved to be a valuable tool to obtain expert rules. Although a MSE of 3.5 (within a range from 1 - 9 of possible values) cannot be regarded as an ideal result, it is a first step to gain “expert knowledge” about rules to transform SDNN and SD2 to valence values. One important result is that two of the rules obtained through optimization namely, IF sdnn IS low THEN valence IS high and IF sdnn IS midlow THEN valence IS high confirmed previous findings where an inverse correlation between SDNN and valence was reported [Re15].

Our next step will investigate the accuracy in detecting the picture classification based on IAPS ratings as a fitness function for the genetic algorithm. This could yield better results as indicators for academic emotions, or for specific learning situations. To do this, our future investigation should entail a learning context where it can activate emotions occurred during learning.

As there are many features which could be derived from our sensor data, e.g. SCR pulses from EDA or HRV from ECG, we will use classifiers like decision trees to obtain a good feature selection. This could result in a better understanding of derived data, in better predictors for valence and arousal, and it could also help to optimize the promising fuzzy logic approach.

Future studies should further investigate the means to provide a learning support for students in a form of Intelligent Tutoring Systems (ITSs) [Ba10]. As the current studies in learning support system revealed the need of context aware system using physiological data [Du07] [Gi13], a system which uses sensor data and provides context aware learning support including emotional support can help learners persist in their learning or break out from the negative states [DG12]. Therefore, our future works include refining emotion detection along with research on appropriate pedagogical intervention to help learners regulate negative states.

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