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Detecting Affective States Based on Facial Expressions Among Students using an Educational Game for Physics

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Abstract. We built logistic regression models to identify facial action units that are associated with affective states of Filipino students using Physics Playground, an educational game for Physics. We found that facial action units AU1 (Inner Brow Raiser), AU5 (Upper Lid Raiser) and AU6 (Cheek Raiser) are significantly associated with engaged concentration, AU20 (Lip Stretcher) with Frustration, AU12 (Lip Corner Puller) with Delight and AU6 with Happiness. We discuss features in the models and future work.

Keywords: Affect detection, facial expression recognition, Physics Playground

1. Introduction

Affective computing refers to computing that “relates to, arises from, or deliberately influences emotions” (Picard, 1997). One branch of affective computing is affect detection, the automatic recognition of feelings, emotions, moods, attitudes, affective styles or temperament of users while interacting with a computer (Calvo & D’Mello, 2010). When applied to an educational context, affect detection refers to the recognition of student feelings and emotions as they engage in an education-related activity. Within the learning context, emotions relate to student behaviour and achievement, and the overall educational experience (Hascher, 2010; Meyer&Turner, 2006).

Emotion is expressed in several channels: voice, body language, physiology and facial expressions. One of the most referenced tools for the analysis of facially-expressed emotions is Ekman and Friesen’s Facial Action Coding System (FACS), a system that provides a means for measuring facial expressions by detecting a set of muscular actions called action units or AUs. FACS 2002 specifies 9 action units in the upper face and 18 in the lower face. In addition, there are 14 head positions and movements, 9 eye positions and movements, 5 miscellaneous action units, 9 action descriptors, 9 gross behaviors, and 5 visibility codes (Cohn, Ambadar & Ekman, 2007). FACS does not impose the emotion associated with the measurements hence it can be objectively used to find which action units or combination of facial actions that are activated while an affect is displayed. Table 1 shows the action units that are recognized by FACET, the software that we use for this study.

Ekman also believed that ones’ action can be anticipated from the facial expression (Duffy 2002). However, there has been very few studies conducted on affect detection using facial expressions in in-situ learning environments as opposed to laboratory settings that support Ekman’s belief. But, studies using other modalities such as data logs from interaction in an educational software combined with observer judgments on affect and behaviour have shown the effects of emotion in learning. In particular (Baker, D’Mello, Rodrigo & Graesser 2010) and (Lee, et.al, 2011) find boredom to be negatively correlated with learning and may lead to problematic behaviour such as gaming the system. Confusion may be beneficial for learning (D’Mello, et.al, 2014) but prolonged state of confusion may lead to frustration and may eventually lead to disengagement and boredom which may further result to the learner giving up (Craig, et.al., 2004; D’Mello et.al., 2011; Liu, et.al, 2013). However, frustration may not always be detrimental to learning but may lead to better understanding of the material and good achievement scores (Pardos, et.al., 2013).

Table 1 Action Units Recognized by FACET

Action Unit	**Description**	**Action Unit**	**Description**
AU1	Inner Brow Raiser	AU15	Lip Corner Depressor
AU2	Outer Brow Raiser	AU17	Chin Raiser
AU4	Brow Lowerer	AU18	Lip Puckerer
AU5	Upper Lid Raiser	AU20	Lip Stretcher
AU6	Cheek Raiser	AU23	Lip Tightener
AU7	Lid Tightener	AU24	Lip Pressor
AU9	Nose Wrinkler	AU25	Lips Parted
AU10	Upper Lip Raiser	AU26	Jaw Drop
AU12	Lip Corner Puller	AU28	Lip Suck
AU14	Dimpler		

Our research goal for this study is to examine the relationship between student learning affective states and facial expressions among Filipino learners. In particular, we want to determine which facial action units are directly associated with the different learning affective states that are observed in the classroom.

Affect-aware systems are recently gaining popularity (D'Mello & Graesser, 2014; Calvo & D'Mello, 2010). A learning system that is able to detect the affective state of its users can effectively provide the proper intervention for the learner to maximize learning. However, research in basic emotions suggests that there are cultural differences in the way emotions are expressed (Marsh, et.al., 2003; Elfenbein & Ambady, 2003) As such, there is a need to determine whether facial expressions of learning affective states among students of different cultures are expressed differently. An even better affect-aware learning system will be a system that is able to detect emotions of students of different cultures for it to respond accordingly.

2. Related Work

Past studies among American learners have found associations between AUs and emotions. Listed in Table 2 are the action units that are found to be associated with the learning affective states indicated.

Table 2. List of AUs associated with Learning-Affective State

AU/Combination of AUs	Associated Affective State	Findings of
AU4, AU7 AU1, AU1 & AU4, AU45	Confusion	McDaniel, et.al. (2007) Bosch, Chen & D'Mello, (2014)
AU7, AU12, AU25, AU26	Delight	McDaniel, et.al. (2007)
AU12 AU45, yaw (head orientation) AU4	Frustration	McDaniel, et.al. (2007) Bosch, Chen & D'Mello, (2014) Grafsgaard,et.al. (2013)
AU1, AU2, AU4, AU14	Engagement	Grafsgaard,et.al. (2013)

Ekman believed that the basic emotions happy, sad, anger, fear and disgust are universal (Ekman, 1992). A happy face in one country will be manifested with the same facial muscles in people in other countries. Taduran (2012) tested Ekman's universality hypothesis on facial expression judgment by applying cross-cultural agreement tests on Filipinos. His findings showed strong cultural agreement on the recognition of happiness, sadness, anger, disgust and surprise. However, for the case of affective learning states, the literature on Filipino learners have only identified what are the academic emotions Filipino college students are experiencing (Bernardo, et.al., 2009). The learning-affective states that are considered in the current study have been identified as part of the emotion words that Filipino students associated with learning. Our broader goal for this research is to be able to determine if there are differences in the way learning-affective states are exhibited by the learners' facial expressions in different geographic locations. In this study, our specific focus is in uncovering which facial features are associated with the learning-related affective states of Filipino learners.

3. Methodology

3.1 Physics Playground

Physics Playground (PP) is a two-dimensional computer game that is designed for high school students better understand physics concepts related to Newton's three laws of motion: balance, mass, conservation and transfer of momentum, gravity, and potential and kinetic energy (Shute et al., 2013). Players are presented with a series of challenges in which players draw using the mouse, and their drawings become part of the physics environment. The core mechanic of the game is to guide a green ball to a red balloon by drawing physical objects and simple mechanical devices (i.e., ramp, lever, pendulum, springboard) on the screen that come to life once drawn. The example level of PP shown in Figure 1, for example, requires a pendulum as its solution. Everything obeys the basic rules of physics relating to gravity and Newton's three laws of motion (Shute et al., 2013).

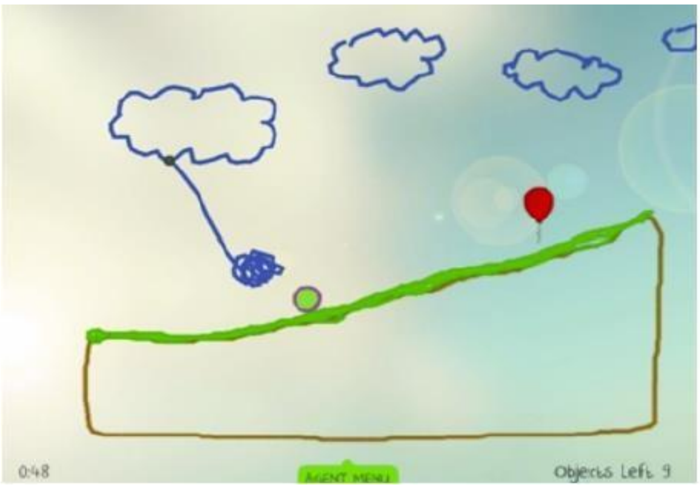

Figure 1: Example level of Physics Playground

The 74 levels in PP encourage the player to solve levels in different and creative ways that adhere to the laws of physics via drawing different simple machines, representing agents of force and motion: inclined plane/ramps, levers, pendulums, and springboards. A ramp is any line drawn that helps to guide a ball in motion. A ramp is useful when a ball must travel over a hole. A lever rotates around a fixed point, usually called a fulcrum or pivot point. Levers are useful when a player wants to move the ball vertically. A swinging pendulum directs an impulse tangent to its direction of motion. The pendulum is useful when the player wants to exert a horizontal force. A springboard (or diving board) stores elastic potential energy provided by a falling weight. Springboards are useful when the player wants to move the ball vertically. In addition, players can create their own levels and watch replays of how they completed a level (Andres et. al., 2014).

3.2 Data Collection

Data were collected from 60 grade 7 students (20 male, 40 female) between ages 12 to 14 from a private school in Davao City, Philippines. In the Philippine Educational System, Grade 7 is the first year of Junior High School. Inexpensive webcams were mounted at the top of each computer monitor. At the start of each session, the webcam and its software were configured so that the students can adjust themselves in a position where their face is at the center of the camera's view. All instructions were given by the experimenters who also served as field observation coders.

3.2.1 Affect Observation

Student affect and behavior was collected using the Baker-Rodrigo-Ocumpaugh Monitoring Protocol (BROMP), a method for recording quantitative field observations, described in detail in (Ocumpaugh, Baker, and Rodrigo, 2015).

The affective states observed within Physics Playground in this study were engaged concentration, confusion, frustration, boredom, happiness, delight, curious, excited, hope and anxious. The affective categories were drawn from (Ocumpaugh, Baker, and Rodrigo, 2015).

Participants were divided equally between three BROMP-certified observers present per session. Students were observed in groups of 15, giving each BROMP coder 5 students to observe per session. Students were observed in 5 to 8 second intervals throughout the 90-minute observation period, resulting in at least two observations per student per minute. If the student exhibited two or more distinct states during his or her respective observation period, the observers only coded the first state.

The observers recorded their observations using the Human Affect Recording Tool, or HART. HART is an Android application developed specifically to guide researchers in conducting quantitative field observations according to BROMP, and facilitates synchronization of BROMP data with educational software log data. The BROMP Manual gives a thorough discussion on how the behaviour and affective states are judged.

3.3 Model Building

Emotient FACET provides five categories of information from raw video data input (https://imotions.com/emotient/). Data exported includes the head orientation, facial landmark location (nose, eyes, lips), basic and complex emotions, the likelihood estimates of the presence of the 19 actions units of the face, and the respondents' gender and whether or not the respondent wears glasses (Facet Manual from emotient.com). In this study we only used two categories of data from FACET logs, the head orientation which tells whether a face is detected or not and the estimates of the 19 facial action units. Our FACET data was exported at a frame rate of 12.5 frames per second. This resulted to an average of twelve rows of information per second.

Around twenty percent (19.9%) of the synchronized data was discarded either because there was not enough valid data (at least one second of face must be detected) or there was no face detected for the entire window. Since we captured data in a naturalistic environment, several factors can cause face registration errors: a lack of good lighting, face was out-of-frame, obstructions such as hands, fast head movements, etc.. Furthermore, six cameras failed to record at all. Hence we only had 54 FACET data logs and thus the participants without the FACET logs are not included in the analysis.

We synchronized the FACET and affect logs using the timestamps for alignment. Similar to the studies of Kai, et.al, we created datasets for five different window sizes (3, 6, 9, 12, and 20 seconds). The window ends at the time the affect log was observed and the window starts at the affect log time minus the window size minus 1. For example in a 3-second window, if the affect log was taken at time 08:00:30 (*hour:minute:second),* we computed for the maximum, mean, median and standard deviation by aggregating the data at the rows 08:00:28 to 08:00:30. For each window size, we obtained the maximum, median, mean and standard deviation for each of the action units. A total of 78 features were created.

To create the datasets for our logistic regression models, we collapsed the computed values for each of the affective states by taking the mean in each of the computed features for each of the participants. For example for the affective state Engage Concentration, we computed the mean of all the concentrating rows in each feature. Then for the NOT Engage Concentration values, we computed the mean for all the rest of the affective states' rows (meaning all other affective states observed was combined). In this study, we only built models for five out of ten affective states because the other five was not observed in at least 50% of the participants in the study. However, the rows for these affective states were included in the aggregated values for the negated behaviour. Note that our dependent variable is the observed Affect.

The logistic regression is a form of regression used when the independent variable takes only two values. In this study we used Affect as our dependent variable. For each of the affective state, we tried to find which facial action units are its predictors. The odds ratio is important in the interpretation of the logistic regression model. The odds ratio is the probability that the facial action unit is present divided by the probability that it is not. In the results presented in this study, the odds ratio column contains predicted changes in odds for a unit change of the predictor. If the value is greater than 1, then it indicates that as the facial action unit predictor increases, the odds of the outcome (that is, the affect) occurring increases. When the value is less than 1, it indicates that as the predictor increases, the odds of the outcome occurring decreases (Field, 2012). Note that in each of the affective states, it is important to set the baseline category. For the Concentrating affective state, we set the presence of the affect as the baseline because it is the expected and most prevalent affective state. For the rest of the affective states, the absence of the affective state was the baseline category. In doing so, the model coefficients reflected the probability of the presence of the outcome affective state.

In building the predictive models, we employ backward stepwise regression method using the Bayesian Information Criterion (BIC) in assessing the goodness of the fit of the model. BIC is computed based on the maximum likelihood estimates of the model parameters. In maximum likelihood, the parameters are estimated so that under the model, the probability of the observed data would be as large as possible. Predictive relationship between Affect and the resulting predictor variable is assessed by the model chi-square statistic.

We used the open source R statistical software in our analysis (https://www.r-project.org/). In the next section we discuss the facial action units that may predict the most prevalent affective states.

4. RESULTS

A total of 5,149 affect and behaviour observations were collected. On-task behaviour comprised 96% of the data, the remaining 4% is composed of off-task behaviour, stacking and Without Thinking Fastidiously (WTF). The prevalent affective states were: Concentrating at 76%, followed by Frustrated at 7%, Confused at 6%, Happy at 5%, Delight at 2% and the other five affective states combined at 4%.

Table 3 shows the list of observed affective states and the percentage of the participants exhibiting them.

Table 3. Percentage of population exhibiting the Observed Affective States

Affective State	Percentage of Population Displaying the Affect
Concentrating	100%
Frustrated	89%
Happy	80%
Confused	78%
Delight	72%
Curious	44%
Bored	33%
Excited	15%
Surprised	15%
Hope	11%
Anxious	2%

All our participants exhibited the Concentrating affect whereas eighty-nine percent showed frustration at some time in the activity. A good eighty percent showed happiness while seventy-eight percent got confused and seventy-two percent were at some point delighted. We have created logistic regression models for these five affective states as they are prevalent in our data.

We found two sets of features that are correlated, AU1*(Inner brow raiser)* and AU2*(Outer brow raiser)* (r=.74) as well as AU6*(Cheek Raiser)* and AU12*(Lip Corner Puller)* (r=.75). We choose to input only one of the correlated features and the decision on which feature to include is based on whether the feature was found to be a predictor of the affect being modelled in previous studies.

For each affective state and for each window size, we computed the max, mean, median and standard deviation. Here we will present the best fitting models generated by R.

Table 4 shows the statistically significant models for the computed maximum value on the window size indicated for the affective state Engage Concentration. The Cheek Raiser AU6 consistently appeared to be significantly associated with Engage Concentration. The odds ratio is highest at the 3 second window meaning it is highly likely that a student is in an engage concentration state with the appearance of the associated action unit at this short instant of time.

Table 4 Concentrating Datasets (Maximum)

Window Size	Intercept	Predictor	BIC	Odds ratio	χ^2	P
3-seconds	0.15	1.10*AU6	150.64	3.00	11.32	<.01
6-seconds	0.10	0.76*AU6	151.77	2.15	7.31	<.01
9-seconds	-0.22	0.68*AU6	152.40	1.96	6.69	<.01
12-seconds	-0.26	0.51*AU6	151.85	1.67	4.4	<.05

Table 5 shows the models created using the computed median values for the indicated window sizes. Note that at the 9-seconds window we have AU1, the Inner Brow Raiser to be significantly associated with Engage Concentration with almost same odds of appearing with the AU1.

Table 5 Concentrating Datasets (Median)

Window Size	Intercept	Predictor	BIC	Odds Ratio	χ^2	p
3-seconds	0.94	1.42*AU6	151.84	4.15	7.24	<.01
6-seconds	0.89	1.25*AU6	154.85	3.5	4.22	<.05
9-seconds	1.01	1.36*AU1	155.10	3.9	3.97	<.05

Table 6 lists the models for the computed means in the window size indicated. We see AU5 the Upper Lid Raiser to be significantly associated with engage concentration which may indicate that students were opening their eyes wide for a brief period looking at their screens.

Table 6 Concentrating Datasets (Mean)

Window Size	Intercept	Predictor	BIC	Odds Ratio	χ^2	p
3-seconds	0.97	1.51*AU5	151.00	4.53	8.09	<.01
6-seconds	0.87	1.34*AU6	153.85	3.83	5.24	<.05
9-seconds	0.93	1.41*AU6	154.08	4.12	5.01	<.05

Table 7 shows the models for the computed maximum values in the listed window for the Frustrated affective state. The Lip Stretcher AU20 emerged to be significantly associated with frustration. There were no other models created for the rest of the datasets in the Frustrated affective state.

Table 7 Frustrated Datasets (Maximum)

Window Size	Intercept	Predictor	BIC	Odds Ratio	χ^2	p
3-seconds	0.56	1.69*AU20	135.54	0.18	6.67	<.01
6-seconds	0.85	1.82*AU20	135.96	0.16	6.25	<.01

Table 8 lists the models for the computed maximum values in the window sizes indicated in the Happy affective state. We found AU6 to be significantly associated with Happiness. It is surprising that we get AU6 (Cheek Raiser) again as a predictor which is similar to the Concentrating affective state. But comparing the models, the models in the Happy dataset have better values in terms of BIC value. This could mean that the appearance of AU6 is well pronounced in this affective state since the rest of the datasets in the Happy affective state for the median, mean and standard deviation were able to get AU6 as predictor in all window sizes. (However, we decided to not publish the rest of the results in the other datasets to save on space on this article.)

Table 8. Happy Datasets (Maximum)

Window Size	Intercept	Predictor	BIC	Odds Ratio	χ^2	p
3-seconds	-0.74	0.61*AU6	106.93	1.85	9.14	<.01
6-seconds	-0.44	1.00*AU6	110.70	2.73	17.4	<.01
9-seconds	-0.65	0.99*AU6	110.61	2.68	17.5	<.01
12-seconds	-0.72	0.86*AU6	113.22	2.37	14.9	<.01
20-seconds	0.74	-0.62*AU6	107.70	0.53	9.14	<.01

Table 9 shows the model for the Delight affective state from the computed maximum values in the 20 second window. This is the only model derived from all the datasets of the Delight affective state. Here AU12 (Lip Corner Puller) came out to be significantly associated with Delight.

Table 9. Delight Datasets (Maximum)

Window Size	Intercept	Predictor	BIC	Odds Ratio	χ^2	p
20-seconds	-1.3	0.67*AU12	97.73	1.95	4.98	<.05

We did not find any predictor for the Confusion affective state in any of the datasets.

5. DISCUSSION

Engaged concentration is the affective state that we want our students to be in at all times. It can be taken as the baseline of learning-affective states. We may be able to use it in distinguishing the other affective states. The dataset for engage concentration in this study is well represented in the sense that all our participants were exhibiting it. A total of 76% of all the affect logs are engage concentration. Three facial features emerged as significantly associated with engaged concentration, AU1, AU5 and AU6. It is surprising that AU6 consistently came out as strongly associated with engaged concentration in all the datasets because AU6 denotes a happy face. This could mean that students were happily engaged with the activity and the learning environment. We attribute this to the fact that game-like software is not commonly used for teaching inside classes in the Philippines. We also note that AU1 was found to be associated with engagement in the study of Graafsguard et al. (2013).

Frustration is associated with AU20 (Lip Stretcher). Though 89% of our population exhibited frustration, on average each of the students only experienced frustration at around 8% for the entire duration that they were observed. In the study of Hoque, McDuff & Picard (2012) they observed smiles in frustration but not the same smile as a delighted smile. The Lip Stretcher, AU20, most likely fit this description of a frustrated smile. We note however, that AU20 was not found to be associated with frustration in previous studies. As such Filipino learners seems to exhibit a different facial expression when frustrated compared to American learners.

Happiness was consistently associated with AU6 (Cheek Raiser) in all time windows and in all datasets even though the students were observed to be in the happiness state at only 7% for the whole duration. We suspect these are the times when students successfully solved the problems in the game and they were truly happy at that instant such that AU6 was well pronounced in the participants' faces. According to Ekman, the prototypical facial expression of happy is evident by the activation of AU12 with or without AU6 (Ekman, et.al, 2002). Happiness being a basic emotion is believed to be universal and our result somehow confirms this as our participants showed the presence of AU6. The absence of AU12 could be due to the fact that the students are in a class performing an activity and at the same time they are being observed, hence we believe the students are controlling their emotions and thus the intensity of the facial expressions may not be perfectly the same as the universally known prototypical face which are mostly exaggerated expressions of the basic emotions.

The affect observers have agreed on how they will differentiate happiness from delight. They decided that delight will be some sort of exaggerated happiness without the surprise indicators. We found one feature associated with delight at the 20-second window, the AU12 (Lip Corner Puller). It is surprising that the model for delight was at the 20-second window as we don't expect delight to last that long. The prototypical facial expression of surprise is comprised of three components: eyebrow raising (AU1/AU2), eye widening (AU5), and mouth opening/jaw drop (AU25/26) (Ekman, et.al, 2002). We note that our result agrees to the observers' definition of delight. We only have AU12 without the AUs of the surprise facial expression. It appears that the American learners' facial expression of delight is more intense compared to the Filipino learners due to the presence of AU25/26 among American learners. This could partly be due to the presence of the observers and the Filipino's culture of timidity in the presence of visitors and their being more respectful to their teachers (Bulatao, 1964; Church, et.al, 1992).

Though confusion was exhibited by 78% of our population and was observed at 7.5% the whole time in each of the participants, we did not arrive at a model. We attribute this to the fact that game-like educational software is a new experience to the students and they were enjoying the activity as evident by the presence of AU6 in the engage concentration state. This resulted to facial features that are not strong enough to come up with a model for confusion.

6. CONCLUSION

We have identified facial features that are significantly associated with some of the learning affective states (engaged concentration, frustration, delight and happiness) that are prevalent in a natural learning environment. Though our models are modest in terms of fit, this is understandable due to the many challenges in doing this study. Some data were removed due to the challenges in taking data in in-situ learning environments where students behaved normally during data collection. They were free to view their classmates monitor, or talk to their classmates or to go take comfort room breaks. Another reason could be the number of participants and the duration of the data collection. This resulted to a limited number of instances for some of the affective-states. However, this serves as a good start as this is the first study in this part of the world to look at the facial features to detect learning affective states. In future work we will look into the data in other parts of the country and compare it to the findings in other parts of the world to know what are the differences and similarities in the facial expressions inside learning environments.

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