Lecture Improvement Using Students Emotion Assessment provided as SaS for Teachers

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***Abstract*—The paper deals with the Cloud Based solution and experience using Microsoft Azure Emotion Assessment Software as a Service embedded for application for teachers. The project was also about testing an assessment on the selected database and accuracy this process was calculated. The paper report about the problems related to camera lighting and resolution of the audience. The testing Azure platform was very good in accessibility and upload of images for almost real-time processing. The further development of this research is leading to provide teachers an effective tool for feedback their audience attention during lecture which should be in correlation of teaching effectivity.**

I. INTRODUCTION

In the last few years the facial emotion assessment phenomena appear in almost every field of research or business involving human communication or interaction. The usefulness of emotional information in evaluation processes is undoubtedly high due to provision of additional information involved in the communication process or determination of human mental states [1][2][3][4]. However, the perception of facial emotions can be viewed as a complex task in the context of non-obtrusive emotion recognition of crowds i.e. recognition by visual information from camera. Studies [5][6] tackled most of the problems of crowd emotion recognition, however, precise facial emotion recognition is still a challenge while for sufficient facial feature extraction the observed face/faces usually should be of a good quality by the means of dimensions, granulation, and lighting conditions [7].

Nowadays, there are multiple online facial emotion recognition application program interfaces (APIs) available which are able of near real-time face processing at a sufficient levels of face recognition [8][9][10][11][12] [13]. In most cases these solutions also achieve sufficient facial emotion scores even on low quality facial images from which it is possible to derive approximate emotional polarity based on the assessed emotion scores.

In this paper we propose a solution to one of the applications where the crowd facial emotion recognition can be used in the form of approximate emotional atmosphere polarity detector is the teaching or lecturing environment.

II. RELATED WORK

During the last decade the education techniques have approached to a new level by inclusion of new technologies (such as emotion assessment) in the teaching process. However, this step lead to creation of a subfield of e-learning [14] rather than enhancement of the classic (lectures, presentations, tutorials, workshops) education techniques and evaluation. Naturally, by the advance of information technologies it was necessary to upgrade equipment in schools or teaching facilities, but it has only a minor impact on the education processes which have remained more-less the same. Until recently, the use of

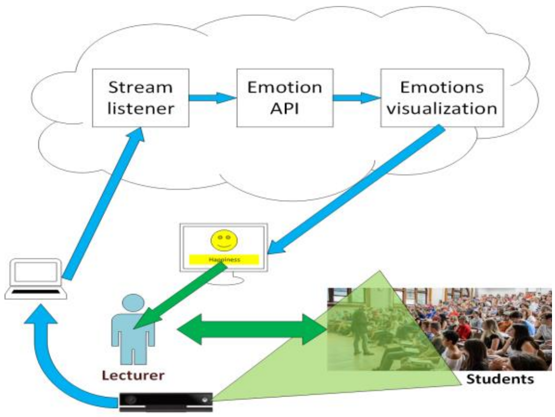

Figure 1. Simplified diagram of the proposed cloud-based affective learning solution. The blue arrows represent the dataflow, the green arrows represent interactions.

sophisticated algorithms and evaluation techniques was solely the domain of specialized education where the learners suffer from various syndromes, disorders, dysfunctions, or develop-mental delays [15][16][17].

Early studies of e-learning [18] and artificial tutoring agents [19][20], which emphasized on the role of emotions during the teaching process established a field which is more lucrative nowadays than it was in the past. In [21] the authors precisely describe the function of emotions during the educational process and offer steps to successfully pass on knowledge contained in academic teaching materials during lecturer-to-student interaction. In this paper, the authors also mention affect-sensitive learning or affective learning is a meta for multiple modern educational and e-learning solutions such as [22][23][24].

However, the affective lecturing process does not have a firmly established evaluation mechanism and the evaluation of emotions is often subjective. A possible multilevel approach for affective learning evaluation was proposed in [25] where the authors investigated eight teaching characteristics (understand-ability, illustration, enthusiasm, fostering attention, lack of clarity, difficulty, pace, level of expectation) and derived two factors: supportive presentation style and excessive lesson demands.

III. CLOUD-BASED AFFECTIVE LEARNING

The Figure 1. shows the simplified version of our proposed cloud-based affective learning solution. Placing this setup in a lecturing environment (classroom or auditorium with an audience facing towards one point) it can provide emotional polarity feedback assessment of the audience. Since, the lecturing process is continuous the lectures pace, content, the audience's attention and emotions can change in time the feedback is also continuously provided in an enclosed loop. In the case of affective learning the lecture can be viewed as an interaction or communication between the lecturer or presenter and the students or audience.

Despite the fact that it is in some cases unacceptable for students or audience to intervene to the lecturing process and give an direct accurate complex feedback orally (usually because of time factor or large number of lecture participants) the lecturer can still use visual information (for example facial emotions and engagement of the audience) to rate his own performance. This process is present in almost every human-to-human interaction where both sides consciously or subconsciously evaluate the additional visual emotional information which is also called the affective loop [26]. Our solution works in a similar way except it does not interact directly with the audience but relies on the lecturer to make a decision and act accordingly based on the feedback from the cloud-service.

A. Emotions in Affective Learning

For the purposes of giving emotional polarity feedback we use only facial emotion assessments provided by Microsoft Emotion API [8] which was chosen for emotion recognition. Even though, other solutions mentioned return the same length emotion vector with Ekman emotions [27] as the MS Emotion API and some were able to outperform it by the means of speed of recognition we have chosen the MS Emotion API because of the emotion confidences precision (double precision values).

From our experiments we learned that the most dominant facial emotion during lectures was the "neutral" face expression. To avoid the monotonous visualization of a single emotion polarity (in the case of the neutral emotion possibility of almost no information value due to constant emotional state) we had to consider the combination of low valued facial emotion assessment confidences and monitor their influence on the polarity. Therefore, the precision of emotion assessment values is crucial while the aggregation towards atmosphere polarity is performed over several facial emotions, the presence of small rates of multiple non-dominant emotions can change the resultant emotional polarity.

We have defined simple aggregation equations for emotional atmosphere polarity assessment which create a modified version of an emotional circumplex model [28]. These circumplex models implement arousal and valence rates of emotions which in our case indicate engagement and polarity. The polarity is a classification of emotions to two distinct classes based on positivity or negativity of emotions [29]. In our case we indicate polarity as follows:

$$\rho_t = \sum_{i=1}^{N}\left(\frac{\sum_{k=1}^{K} p_{ik}}{K}\right) - \sum_{j=1}^{M}\left(\frac{\sum_{j=1}^{K} n_{jk}}{K}\right), \qquad (1)$$

where ρ_t is the immediate polarity coefficient, N represents the number of positive emotions, M represents the number of negative emotions, K is the number of recognized faces, p and n are the positive or negative emotion values where $n, p \in \langle -1,1 \rangle$. Note that this equation is usable for any emotional model where it is possible to differentiate between positive and negative emotions. After extracting the immediate polarity coefficient it can be used as a time independent feedback. This response is useful for single non-consecutive frames or images.

However, it is possible to enhance the polarity measurement by involving the time constant. If we have a number consecutive images i.e. a video stream, we are able to add a relation between two consecutive emotion polarity measurements. The existence of this relation is based on our assumption that the emotions slowly degrade back to a "neutral" state and that consecutive emotion measurements affect each other. Moreover, we need to implement a mechanism which will automatically adapt to the growing or lowering engagement. Therefore, we propose another two equations, which apply a linear scaling factor and adaptive engagement normalization for both arousal and valence coefficients:

$$\alpha_t = \gamma\alpha_{t-1} + \frac{2K - K_m}{K_m}, \qquad (2)$$

where α_t is the arousal coefficient where $\alpha_t \in \langle -1,1 \rangle$, γ is the engagement scaling factor which we set low ($\gamma = 0{,}05$) hence the engagement value decreases much quicker than the emotion polarity value, K is the same as in (1) the number of recognized faces, and K_m is the maximum number of faces measured.

For valence:

$$\beta_t = \omega\beta_{t-1} + \frac{2\rho_t - 3K_m(N+M)}{NK_m + MK_m}, \qquad (3)$$

where β_t is the arousal coefficient where $\beta_t \in \langle -1,1 \rangle$, ω is the polarity scaling factor ($\omega = 0{,}6$), ρ_t is the measured immediate polarity, N and M are the numbers of positive and negative emotions, K represents again the number of recognized faces, and K_m is the maximum number of faces measured.

B. Cloud service for Affective Learning

The common advantage of cloud-based solutions lies in easy management of resources with multiple on-demand services which allow quick and reliable deployment of services. This is also true for emotion recognition solutions.

We used the MS Azure Cloud's Cloud Service [30] which provides simple deployment of native .NET applications directly from the Visual Studio IDE. By choosing the MS Azure Cloud Service we got infinitely scalable service with load-balancing which keeps the application highly available even under heavy loads (several thousands of users). Moreover, MS Azure offers secure and fast connectivity to its products thus providing background for real-time applications.

IV. Experiments

In this paper we present two evaluation experiments which prove the usability of our solution. Notably, the sufficient emotion assessment performance of the Microsoft Emotion API and the suitability of our solution for emotional atmosphere polarity assessment and engagement rate in a real world experiment.

TABLE 1.
CONTINGENCY TABLE OF THE EMOTION ASSESSMENT RESULTS OF THE MICROSOFT EMOTION API OF THE KDEF DATABASE

	A	C	D	F	H	N	SA	SU	SUM	Recall
A	**63**	1	9	1	0	55	10	0	**139**	0.45
C	0	**0**	0	0	0	0	0	0	**0**	0
D	9	0	**101**	1	1	3	24	0	**139**	0.73
F	0	3	7	**26**	3	17	32	47	**135**	0.19
H	0	0	0	0	**136**	0	0	0	**136**	1
N	0	0	0	0	0	**134**	2	0	**136**	0.99
SA	0	0	0	0	1	19	**117**	0	**137**	0.85
SU	0	0	0	0	3	10	0	**126**	**139**	0.91
SUM	**72**	**4**	**117**	**28**	**144**	**238**	**185**	**173**	**961**	
Precision	0.88	0	0.86	0.93	0.94	0.56	0.63	0.73		

A - anger, C - contempt, D - disgust, F - fear, H - happiness, N - neutral, SA - sadness, SU - surprise

A. Microsoft Emotion API performance evaluation

Hence, our solution strongly relies on the performance of the Microsoft Emotion API's emotion assessment we have created an evaluation experiment. In this experiment we used the Karolinska Directed Emotional Faces (KDEF) database [31] which consist of 4900 faces with classic Ekman's emotion model labels. However, we needed to trim this database of rotated faces while our solution uses only upright frontal faces for emotional atmosphere polarity assessment and engagement evaluation.

It is necessary to note that the original vector returned from the Microsoft Emotion API consisted of eight emotions instead of seven in the classic Ekman's model. This is due to the "Contempt" emotion which was left out from the evaluation process. Furthermore, for the comparison with the reference label of the database we have selected the dominant emotion label of the vector by selecting the emotion with maximum value of confidence.

The TABLE 1. contains the results of the evaluation. The measurements indicate an accuracy rate of 73.2%. We consider this as sufficient for emotional polarity assessment, hence the lower precision of recognized emotions is mainly caused by higher confidence values caused by possible presence of other emotions.

B. Lecture emotional atmosphere polarity assessment

For a real world experiment we decided to test the solution on a lecture with 45 students which took place at our university. We have created a setup consisting of a Kinect 2.0 sensor for image acquisition in FullHD resolution which was connected to a laptop that was streaming the visual data directly to our cloud service. Since, we wanted to test the performance the feedback from the service was not presented to the lecturer but only stored to a remote computer which accessed the visualization.

The experiment was successful and we gathered feed-back data to various actions during the lecture. In the Figure 2. the results from the lecture are shown and we can easily distinguish various sections of the lecture. We can identify four sections. Introduction – during this part the students were informed about the experiment and were requested to prepare for the upcoming short test. From 0 to 50 around 2,5 minutes. Test – students writing a test. From 50 to 530 around 25 minutes. Pause – students were allowed to leave the lecture room. From 530 to 740 around 10 minutes. Lecture – classic lecture. From 740 to 1750 around 50 minutes. We have carried out number of other experiments in academic environment. The main problem of these experiments are light conditions and resolution of the used cameras and it also depends some of the face identification and emotion assessments. One a face is not identified on the picture no emotional assessment can be produces. The following picture presents some of the cloud based emotion assessment during a lecture in the small group of students.

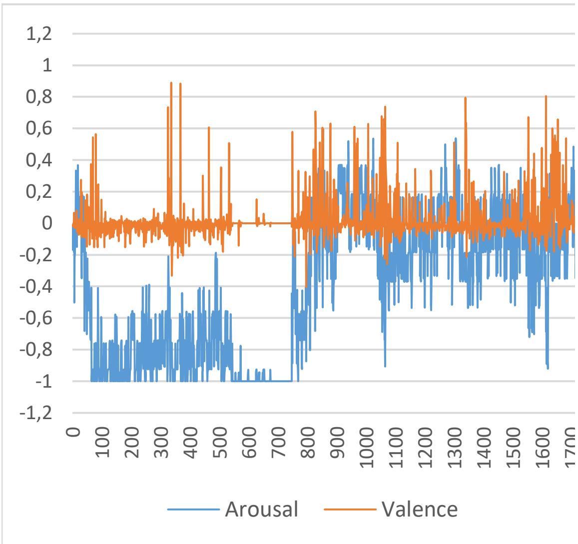

Figure 2. Graph of assessment of emotional atmosphere polarity and engagement rate. The Y-axis is the same for both rates while both are measured in the same range $\alpha, \beta \in \langle -1, 1 \rangle$. The X-axis shows the time factor measured in discrete values which represent

V. Conclusion

Emotional Assessment service on the cloud has a great application potential. The emotion estimation of the human is based mostly on image processing and therefore there are number of problems incorporated with image processing, face identification and ability to cover number of space in front of camera. The speed of image upload to the cloud is getting better and we can generate the emotion assessment of the human by really fast speed under 100 milliseconds and could be part of number of application in learning enhancement, human robot interaction, number of business applications and many others. Teaching by having estimation of the emotional status of the students or listeners will be more precise with engagement of other type of biophysical sensors to improve a classification accuracy of the cloud based software as a service.

Figure 3. Examples of the emotion assessment during a lecture in small class lecture.

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