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Automatic recognition of student emotions from facial expressions during a lecture

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ABSTRACT

Emotions are of great significance in education as in all areas of human life. It is acknowledged that, although the cultures of people, the environment where they live, and the language they use vary, emotions that are evaluated as universal do exist. In this study, we examined the changes in the emotions of 67 students during the lectures of Basic Information Technologies who studied in three different departments in a state university in Mediterranean region. The facial expressions of the students were analyzed and digitalized in terms of the feelings of disgust, sadness, happiness, fear, contempt, anger and surprise by means of a software developed through Microsoft Emotion Recognition API and C # programming language. During the lecture, we studied how student emotions varied and whether this change was statistically significant according to their departments, gender, lecture hours, the location of the computer in the classroom, lecture type and session information. The lesson plan consisted of three stages: introduction, activities and closure. The significance of the difference in emotions and the relationship between emotion change and achievement were examined according to three different stages. The research showed that feelings of contempt, anger, fear and confusion increased, while feelings of happiness, sadness and disgust decreased in the first stage of the lecture. It was determined that the feeling of happiness increased rapidly, whereas all other emotions decreased during the closure section of the lecture. We found that only the feeling of sadness displayed a significant difference according to the departments. It can be suggested that the equipment that provides instant feedback to the lecturer by monitoring the students' emotions automatically throughout the lecture can be made available throughout the educational institutions, thus contributing to the increase in the quality of education.

1. Introduction

Learning is made up of four components: knowing, planning, practicing and reflecting (Johnson, 2000). Planning is considered as a substantial part of learning. Farrell (2002) argued that an effective lesson plan can achieve lesson objectives which are stated appropriately and clearly. Maconie (2006) stated that, as in many disciplines, it is vital to focus on the task and maintain this in achieving the educational goals. It is already known that there are a great number of different lesson plan stages. Hunter (1984) advocated the seven-stage lesson plan, and Johnson (2000), on the other hand, the four-stage lesson plan. Farrell (2002), however,

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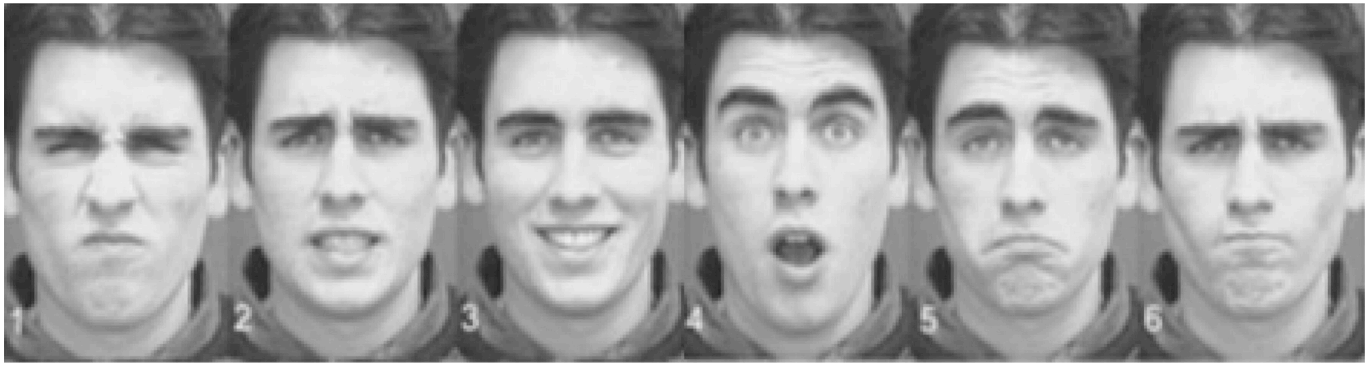

Fig. 1. Basic facial expression phenotypes 1: Disgust 2: Fear 3: Happiness 4: Surprise 5: Sadness 6: Anger (De la Torre and Cohn, 2011).

explained the general components of a lesson plan in five stages: general appearance, encouragement, learning/participation, closure and follow-up. As the lesson plan is essential in the learning process, so is the time allocated to the components in this plan because the typical student's attention span is admittedly not very long. Attention period is defined as the time spent by a person focusing on a task (Beger, 2018). In their literature scan, Wilson and Korn (2007) expressed that the students' attention began to decline after 10–15 min. Lloyd (1968) also stated that understanding peaked in the first 5 min, decreased after 10 min and rose again between the 45th and 50th minutes (as cited in: Wilson & Korn, 2007). Frost (1965) found out that attention was higher in the first 10 min, and that the attention of 10% of the students declined in about 15 min (as cited in: Wilson & Korn, 2007). There are various estimates regarding the continuous attention span for various age groups (Bradbury, 2016; Schaefer & Millman, 1994). Cornish and Dukette (2009) maintained that continuous attention span is up to 8 min, and that this duration varies between 3 and 5 min in children and maximum 20 min in an adult. There have been several studies conducted on the measurement of attention span. There are various studies such as the relationship between the amount of note taken down by the students and attention span (Hartley & Cameron, 1967; Maddox & Hoole, 1975; McKeachie, 1986; McKeachie & Gibbs, 1999), the relationship between the amount of information remaining in the memory of the students at the end of the lecture and the duration of the lecture (McLeish, 1968 cited: Wilson & Korn, 2007), and the relationship between the attention span and the number of heart beats per minute (Bligh, 2000).

Today, the studies reveal that, born and grown up in the digital age, the individuals in the new generation called Generation Z started to use computers at a very young age and have spent a considerable amount of time with digital tools (Oblinger & Oblinger, 2005). It can also be argued that the attention span of the Generation Z, whose expectations differ according to other generations, is also likely to vary. Therefore, in this study, we examined how the emotions of the students changed during a lecture. This research was carried out by means of computerized face analysis technique unlike the previous studies.

Although it was considered, prior to the 1960s, that the facial expressions varied according to the cultures, many studies have revealed that people from different cultures interpret facial expressions in the same way. It was suggested that the facial expressions of disgust, fear, joy, surprise, sadness and anger are universal (Ekman, Rolls, Perrett, & Ellis, 1992). The images of these facial expressions are illustrated in Fig. 1 (De la Torre and Cohn, 2011; Lee, 1994).

There are different approaches in determining facial expressions. One of these approaches is called facial electromyography (EMG) and is performed by placing facial electrodes on different parts of the face, which allow to measure the electrical current from muscle tissues through the skin. In another approach, facial movements can be examined individually or in combination via video recordings. Facial Action Coding System (FACS), developed by Ekman and Friesen for this purpose (1976), enables the identification of visually distinguishable facial movements. In this method, 46 action units are defined for each individual muscle activity of the face. Today, it is possible to perform facial expression analysis with the help of computers as a result of increased processing capacity of computers, having faster computers and more data. As can be seen in Fig. 2, facial expressions result from the change of facial parts such as mouth, nose, eyes and eyebrows that make up facial expressions. Computer-assisted automatic facial expression analysis involves finding the

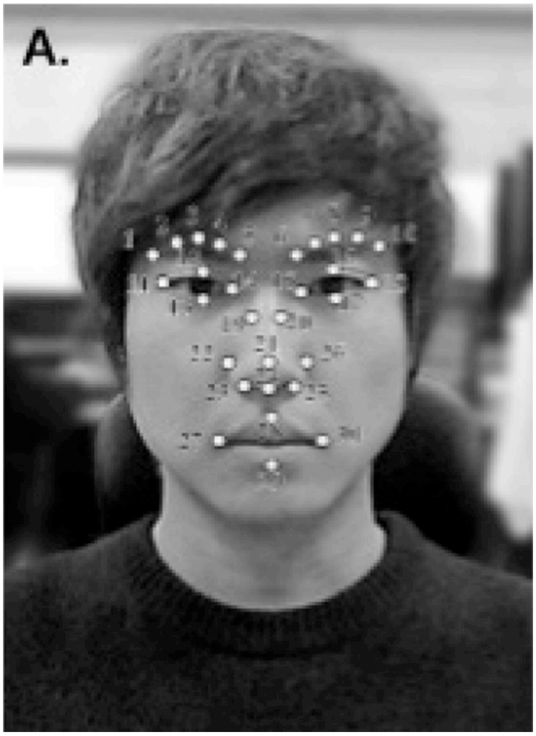

Fig. 2. Facial analysis points (Kim et al., 2015).

face in the image taken from the camera, establishing the attributes of the facial expressions from the face image and interpreting them (Bayrakdar, Akgün, & Yücedağ, 2016).

There are several applications of automatic facial expression recognition in the literature. Kambayashi, Diago, Kitaoka, and Hagiwara (2010) monitored the facial expressions of the drivers to detect fatigue and stress that are thought to cause traffic accidents, and Hachisuka (2013) determined a driver's drowsiness based on facial expressions. Sezgin, Davies, and Robinson (2009) examined the drivers' response to audial and visual stimuli by using speech recognition and facial expression detection methods, and found the performance of the detection based on speech recognition to be very poor in noisy environments, while the performance of the detection based on video was reasonably accurate regardless of ambient noise level. Chickerur and Joshi (2015) studied images from three-dimensional models, suggesting that it would not be possible to obtain a reliable result from the images taken by traditional two-dimensional cameras due to lighting conditions and people's postures. In their study, Krithika and Lakshmi Priya (2016) developed a program to determine the emotions of the students in the e-learning environment by monitoring the head, lip and eye movements. Yang, Alsadoon, Prasad, Singh, and Elchouemi (2018) argued that the automatic facial expression recognition system they developed could monitor students' emotions in distance education applications and allow teachers to develop learning strategies according to the students' emotions. Sharmila and Kalaivani (2018) stated that written and verbal feedback from the students may not give correct information to the lecturer. In order to make the lecture more interactive, they analyzed the video in which they recorded the students' facial expressions during the lecture by using the Support Vector Mechanism method. However, Tang, Xu, Luo, Zhao, and Zou (2015) used K-nearest neighbor (KNN) and achieved an accuracy of 79%. In a study, real-time automatic participation of students from facial expressions was defined. Facial expressions of the students were collected and analyzed during a cognitive training task (Whitehill, Serpell, Lin, Foster, & Movellan, 2014). In some studies, the definition of facial expression recognition in distance learning courses was studied (Cheng Lin et al., 2013; Kim, 2017). Sahla and Kumar (2016) propose a system using deep convolutional neural network technique for students emotions in the classroom. In some studies, different methods of recognizing facial expressions were studied (Liang, 2019; Mao et al., 2019). In another study, a theoretical basis for learning the facial expressions of the students in the classroom from the video and the automatic evaluation of the teacher learning in the classroom was formed (Pan et al., 2018). In the Boonroungrut, Oo, and One (2019) study, cloud-based Facial emotion analysis was conducted to investigate students' feelings in the classroom. For this purpose, the basic chinese course lasted for 5 weeks and included 29 international students. Students' mood changes were examined. In a secondary school in China, it was reported that a similar system was used to monitor students' moods and provide feedback to the teacher (VanderKlippe, 2018). In another study, images were taken via webcam to determine the emotion and alertness of the students. In the study, a system was proposed to help the students to increase the productivity of the students and to provide appropriate interaction and feedback (Happy, Dasgupta, Patnaik, & Routray, 2013). Ayvaz, Gürüler, and Devrim (2017) tried to classify some physiological values in facial images with classification algorithms such as CART, RF, kNN, SVM by performing facial expression analysis of the participants in the e-learning session conducted via Skype software with Facial Emotions Recognition System they developed. At the end of the classification process, they calculated the Happiness, Fear, Sadness, Anger, Surprise and Disgust emotions which were accepted as universal. They have determined the SVM algorithm as the most appropriate method for this process. Khalfallah and Slama (2015) examined anger, sadness, surprise and happiness emotion rates in a virtual laboratory environment. Petrovica and Ekenel (2016), on the other hand, examined the studies on this subject.

Recent developments in neurology have shown that there are connections between emotions and cognitive, and audial functions, meaning that there is a relationship between learning and emotion (Immordino-Yang & Damasio, 2007). Studies indicate that students' emotions are vital during the lecture (Krithika & Lakshmi Priya, 2016).

Wlodkowski(1999) stated that emotions have a negative or positive effect on motivation and therefore emotions should be taken into consideration during learning. Linnenbrink-Garcia and Pekrun (2011) stated that in recent years, the effect of student emotions on learning and class participation has been studied. Cleveland-Innes & Campbell, 2012 state that emotions can help or prevent learning based on previous studies. Emotion can limit learning as a distraction, but if managed, it can also play a supporting role in thinking, making decisions, encouraging and directing (Cleveland-Innes & Campbell, 2012). Different emotions are known to cause different outcomes. While some positive emotions are positively associated with intrinsic motivation, effort, self-regulation and more sophisticated learning strategies (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011), negative emotions such as anger are associated with anxiety and boredom, reduced effort, poor performance, increasing external regulation, and reducing self-regulation strategies (Artino, 2009; Daniels et al, 2009; Pekrun et al, 2009). In a study, it was found that anger and anxiety occurred in children when children perceived their teachers as the direct control object. It was determined that these emotions increased external motivation, which reduced academic participation and encouraged limited participation (Assor et al., 2005). In further studies, anger was defined as the strongest individual predictor of student achievement (Kim, Park, & Cozart, 2014), and It can stimulate the learning experience or give people joy to blind their learning difficulties (Dirkx, 2008). Students who adopt a performance approach experience sadness, anxiety and anger when the goals are not achieved (Pekrun, Elliot, & Maier, 2009). Another feeling is surprise. Surprise is a short-lived feeling. Therefore, it has less effect on increasing persistence in education than emotions of confusion, frustration and boredom (D'Mello & Graesser, 2011). Another feeling is fear. This feeling in the face of uncertainty occurs in students in the online environment (Zembylas, 2008).In the classroom, it was determined that the lack of communication between teachers and students increased emotions such as anger, anxiety, boredom (Mazer, McKenna-Buchanan, Quinlan, & Titsworth, 2014). It was determined that effective teacher communication provided positive emotions such as enjoyment, hope, and pride (Titsworth, McKenna, Mazer, & Quinlan, 2013). In another study, negative feelings such as uch as anger, anxiety, shame, hopelessness, and boredom were related to students' academic achievement, learning organization, and learning strategies (Pekrun, Goetz, Frenzel, Barchfield, & Perry, 2011). In this study, the facial expressions of the students were examined in terms of disgust, sadness, happiness, fear, contempt, anger and confusion by using Microsoft Emotion Recognition API, and the changes in their expressions during the lecture were determined to answer the

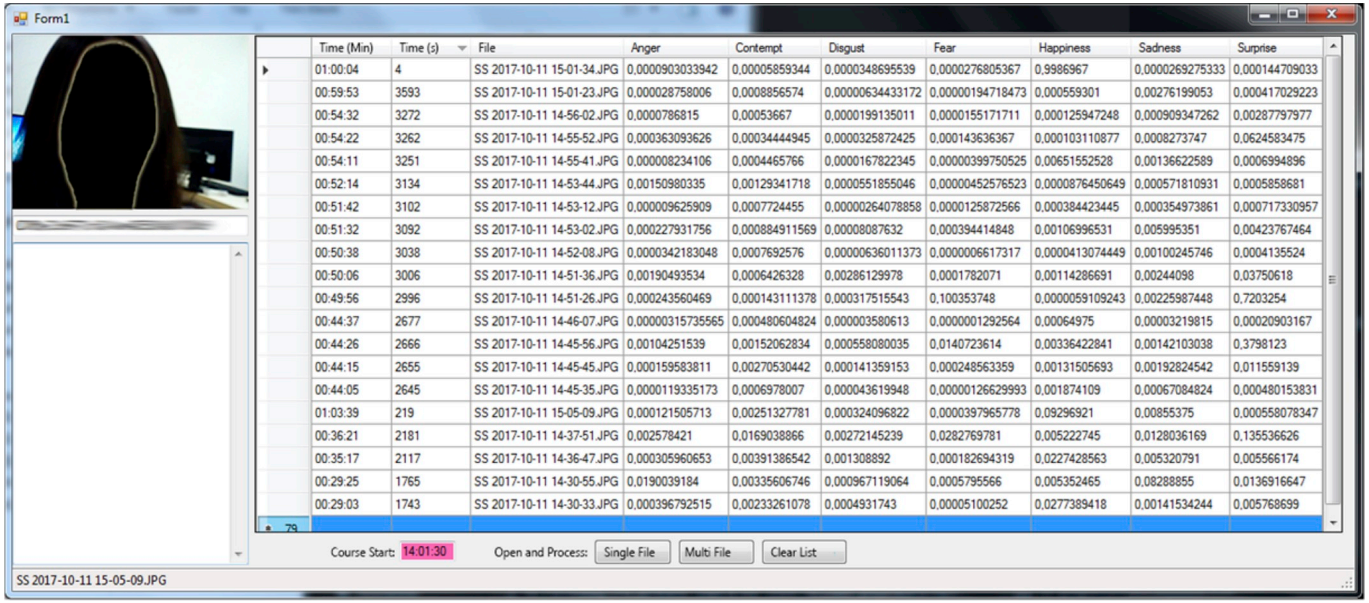

Fig. 3. Data analysis software.

following questions:

1. How do the students' emotions change during a lecture?
2. Do students' emotions differ significantly during a lecture according to
   a. Their departments
   b. Their genders
   c. The class time
   d. The location of the computer in the classroom
   e. The lecture type
   f. The session information?
3. Is there a significant difference in the emotions of the students according to the lecture stages?

Such a study performed with the use of computer-assisted automatic facial expression recognition system is of importance in terms of being based on quantitative data and eliminating the deficiency determined in the literature. With the help of some concrete data acquired in the study, it will be possible to have an idea about the changes in the emotions of the students on the basis of time during the lecture, to give feedback to the educator about how long after the lecture starts their attention decreases due to the change in their emotions, and to contribute to the increase in the quality of education.

2. Method

In this study, facial movements coding system (FACS) was used and the facial expressions of the students during the lectures were analyzed. In this process, the students' emotions were examined in terms of disgust, sadness, happiness, fear, contempt, anger and surprise, using Microsoft Emotion Recognition API. During the lecture, the images containing the facial expressions of the students were collected every 10 s and analyzed with a special software. In order to perform the analysis thoroughly, it is essential that the faces of the students be seen completely. For this reason, cameras were installed on the students' computers and the materials to be used by the lecturer during the lecture were reflected on the computer screens of the students. By doing so, we attempted to create an environment which allowed the cameras to perceive students' faces more properly. Preparations were made before the students came to the classroom, and the cameras and the software that automatically took the images from the cameras were made operational. At the end of the lecture, the recorded photos were collected from the computers. At the beginning of each lecture, the active beginning time of the lecture was noted by the instructor, and by reviewing these records, unnecessary photographs taken from the camera before and after the lecture were deleted.

2.1. Sample group

67 students participated in the study (24 females and 43 males who studied in the Department of Journalism - DOJ ($n = 29$), Science Teaching - ST ($n = 18$), Recreation - RCR ($n = 20$) in a state university in the Mediterranean Region and had Basic Information Technologies in 2017–2018 education year. At the beginning of the study, the instructor informed the students about the study. In the following lectures, it was observed that some students did not prefer to sit at the computers with a camera, whereas others turned the cameras away. Therefore, it was not possible to record the images of all students at all stages of the study.

2.2. Data collection and analysis

After excluding the pictures that could not be analyzed as the faces could not be properly seen, the images of the students obtained through webcams mounted on computers were analyzed with a software which had been developed using C # programming language in Visual Studio and Microsoft Emotion Recognition API. Despite the efforts, there still remained some images that could not be analyzed. Such images were reported to the operator by the Microsoft Emotion Recognition API and no digital values were generated. As a result of the analysis, the emotion involved in each image was transformed into digital data. The screenshot of the software used during the analysis is shown in Fig. 3.

The elements that can prevent the evaluation of the images obtained, such as ambient light, camera image quality, students' height and sitting position while capturing pictures by the cameras to process created some limitations in the study. In addition, the images of the students who covered their mouths or faces with their hands, or stretched while listening to the lecture could not be assessed because their faces could not be seen thoroughly.

Graphics and, when necessary, a statistical software were used in the analysis of the data collected by examining the students' pictures. The effects of different variables on these emotions were analyzed by Manova test. In order to do this, firstly, the assumptions of the Manova test were checked. In the normal distribution, two main components were taken into account: kurtosis and skewness (Tabachnick & Fidell, 2007). Büyüköztürk (2011) stated that, if the skewness coefficient is between ± 1, the data is suitable for normal distribution; however, according to George and Mallery (2003), the data is distributed normally if the skewness and kurtosis values are between ± 2. In the study, data transformations were used to normalize the data since the skewness and kurtosis values did not fall within these ranges (Pallant, 2002). The square root transformation was used for the data. In the Manova analysis, it is expected that there is a moderate relationship between the dependent variables. Tabachnick and Fidell (2007) stated that this value should not be over 0.90. In our study, as the relationship between the variable "sadness" and the other variables was lower than .30, "sadness" was not included in the Manova test and evaluated with the Anova test separately. In the study, Box's M statistics (Green & Salkind, 2008) was used to check for homogeneity of covariance, and Levene test was used to test for homogeneity of variance on the dependent variables. As all the assumptions were met, it was determined by using the Manova statistics whether the emotions of the students changed according to their departments, gender, lecture hours, the location of the computer in the classroom, lecture type and session information. In the data analysis, Bonferroni correction was performed because the students had seven different emotion groups and this value was used to examine whether their emotions differ significantly according to different variables. For Bonferroni correction, 0.05/7 or 0.01 can be used as significance value/number of groups (Norušis, 2002). Therefore, p value was accepted as 0.01 in the study. Anova and *t*-test were used for the analysis of emotions in the stages of the lecture and regression analysis was used for the determination of the relationship between the level of achievement and emotions.

3. Findings

Fig. 4 involves the data variation of the all 67 students regarding the ***first sub-problem*** of the study "How do student emotions change during a lecture?".

The facial analysis software generates decimal values so that the sum of the data collected regarding student emotions is always 1.0. In Fig. 4, the primary axis on the left side of the graph indicates the scales of contempt, anger, fear, and disgust (bold lines); the secondary axis on the right side of the graph displays the scales of sadness, happiness, and confusion (gray lines).

Fig. 4 shows how student emotions changed in seconds. Contempt increased rapidly for approximately 9 min (until the 533rd sec), and decreased for the next 13 min (up to the 1306th sec). It rose again until about the 32 nd min (the 1918th sec) and plummeted until the end of the lecture. Anger increased quite rapidly for about 4 min (until the 237th sec), after which dropped till the 12th minute. Although there was a slight increase afterwards, it started to decrease after the 21st minute (the 1246th sec). In contrast to contempt and anger, sadness decreased for the first 4 min and saw a slight rise up to the 13th minute. Then, it fell again, and increased rapidly between the 26th and 35th minutes, following which plunged. Although happiness saw a slight decrease in the first 4 min of the lecture, there was no significant change until the 13th minute. However, it rose rapidly from the 13th minute to the 26th minute (the 1548th sec). It decreased between the 26th and 34th minutes, after which rose steadily after the 34th minute of the lecture. It can be argued that the patterns of the change in fear and confusion were quite close to each other. With an increase during the first 4 min, they fell slightly and then rose again. After they saw another fall between the 26th - 28th minutes, they increased rapidly, despite the rapid decline after the 37th minute of the lecture. There was no significant difference in disgust throughout the lecture. With slight changes, it saw a decrease in the first 4 min of the lecture, which was followed by slight fluctuations and then after the 34th minute of the lecture it fell again.

Given below is the data for the ***second sub-problem*** of the study, "How do student emotions change during a lecture according to different variables (the students' departments, gender, lecture hours, the location of the computer in the classroom, lecture type, session information)?".

In the Manova analysis for the variance of student emotions according to students' departments, it was found that the homogeneity of covariance matrices (Box's $M = 71.86$, $p > 0.01$) and homogeneity of variance matrices (Levene test anger, contempt, disgust, fear, happiness, confusion $F(2\text{-}61) = 1.750, 0.525, 2.990, 0.299, 0.724, 0.033$, respectively, $p > 0.01$) were met. There was no significant

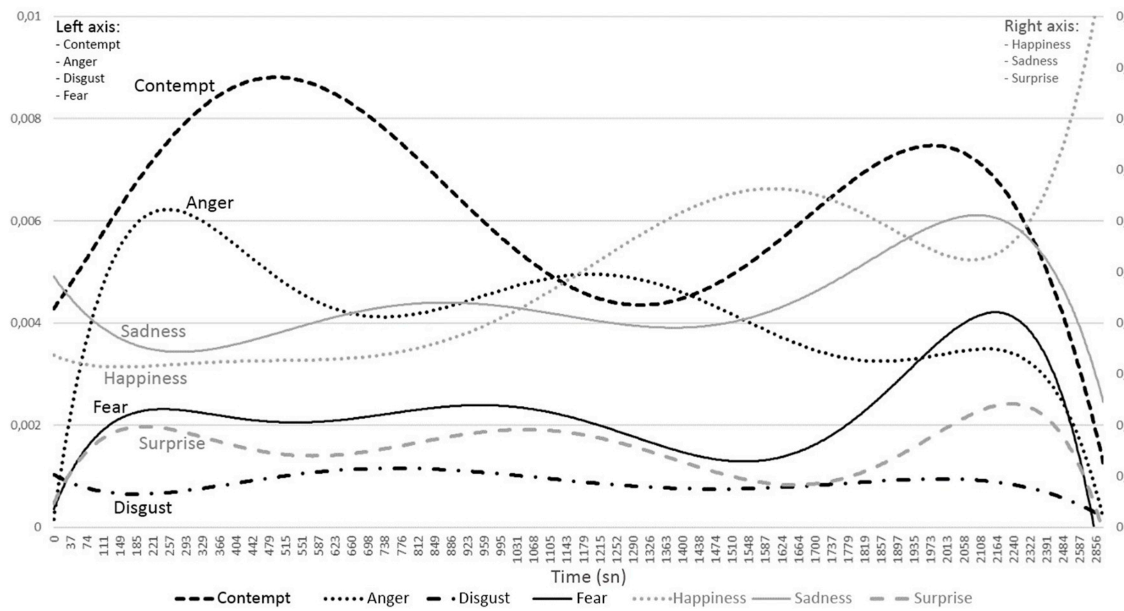

Fig. 4. Change of emotions during a lecture.

difference in the emotional changes according to the students' departments (Wilks Lambda (Λ) = . 593, F = 2.346a; $p > 0.01$).

In the analysis for the variance of student emotions according to their gender, it was found that the homogeneity of covariance matrices (Box's M = 34.428, $p > 0.01$) and homogeneity of variance matrices (Levene test anger, contempt, disgust, fear, happiness, confusion F (1-64) = .253, 0.70, 0.512, 1.481, 2.299, 1.939, respectively, $p > 0.01$) were met. There was no significant difference in the emotional changes according to the students' gender (Wilks Lambda (Λ) = . 850, F = 1.732a; $p > 0.01$).

The computers were placed in the front row, middle row and back row. Multivariate analysis of variance (Manova) was also performed to determine whether the row of the desks affected the changes in emotions. In this analysis, it was found that covariance matrix homogeneity (Box's M = 67.335, $p > 0.01$) and variance homogeneity (Levene test anger, contempt, disgust, fear, happiness, confusion F (2-63) = 1.895, 0.876, 2.394, 0.266, 0.044, 0.526, respectively, $p > 0.01$) were met. There was no significant difference (Wilks Lambda (Λ) = .909, F = .471a; $p > 0.01$) in the emotional changes according to the position of the computer row where the students were seated.

The study was carried out in the lectures based on theory and practice. It was examined whether student emotions changed according to the type of the lectures (theory or practice). In the analysis, it was found that covariance matrix homogeneity (Box's M = 41.072, $p > 0.01$) and variance homogeneity (Levene test anger, contempt, disgust, fear, happiness, confusion, F (1-64) = 2.460, 0.549, 8.247,. 688, 5.201, 1.426, respectively, $p > 0.01$) were met. According to the Manova statistics (Wilks Lambda (Λ) = . 849, F = 1.749a; $p > 0.01$), there was no significant difference in the emotional changes according to the lecture type.

The lectures were held at two different times of the day, morning and afternoon. The change in student emotions according to lecture hours was also examined by Manova statistics. It was found that covariance matrix homogeneity (Box's M = 23.549, $p > 0.01$) and variance homogeneity (Levene test anger, contempt, disgust, fear, happiness, confusion, F (1-62) = .493, 0.045, 0.266, 0.064, 1.042, 0.025, respectively, $p > 0.01$) were met. According to the analysis conducted to determine whether lecture hours affected student emotions (Wilks Lambda (Λ) = . 929, F = .721a; $p > 0.01$), there was no significant difference in the emotional changes.

In this study, the lectures were held in two sessions. After the first session, a 10-min break was given, following which the second session started. In the Manova statistic to determine the effect of session information on student emotions, it was found that covariance matrix homogeneity (Box's M = 27.656, $p > 0.01$) and variance homogeneity (Levene test anger, contempt, disgust, fear, happiness, confusion F (1-64) = 6.836, 0.000, 0.428, 4.529, 0.226, 0.239, respectively $p > 0.01$) were met. There was no significant difference in emotions (Wilks Lambda (Λ) = . 892, F = 1.185a; $p > 0.01$) in terms of the effect of session information.

As the relationship between the students' feeling of sadness and other emotions was below .30, which is a low level, we used Anova test (Table 1) to determine whether there was a significant difference in sadness according to the students' departments and the location of the computers in the classroom; on the other hand, we used T-test (Table 2) to find whether the difference in sadness was statistically significant according to the gender, lecture hours, lecture type and session information.

The results of the Anova analysis shown in Table 1 indicated that there was a significant difference in the students' feelings of sadness according to the department (F (1,61) = 4.497, $p < 0.05$). The Sheffe test showed that there was a significant difference in sadness in the departments of Science Teaching (ST X = .226) and Recreation (RCR X = .161). It is clear that Science Teaching students experienced the feeling of sadness more intensively.

The results of the *t*-test shown in Table 2 indicated that there was no significant difference in sadness according to gender, morning/ afternoon lecture, theory-based/practice-based lecture and session information.

Below are the findings about the ***third sub-problem*** of the research, "Is there a significant difference in the emotions of students according to the stages of the lecture?"

In order to examine whether there was a significant difference in the emotions of the students according to the stages of the lecture, the previously created curriculums (Farrell, 2002) were examined and the researcher formed the lecture plan in three stages in accordance with the plans in the literature. In the first stage of the lecture (0-4th minutes), the teacher entered the lecture, reminded the subjects covered in the previous lecture and drew the attention of the students. In the second stage of the lecture (5th-35th minutes), various learning activities were conducted; whether learning happened or not was controlled; the encouragement and interaction of the students were provided. In the third stage of the lecture (36th-46th minutes) the closure was done; various questions about the subjects learned in the lecture were asked; the subjects to study in the following lecture were discussed. When the data collected in the whole study was examined, it was found that the number of the students who had let their images taken during the three stages of the lecture decreased from 67 to 32. For this reason, the analysis was carried out with the data collected from the 32 students. Each student's mean of emotions were determined for each emotion in the three different stages and this mean was accepted as an indicator of that emotion. "One-way Repeated Measures Anova" was used to determine whether there was a significant change in the emotions (Fig. 5).

Table 1
Changes in sadness according to the department and computer row.

Variable		Sum of squares	df	Mean squares	F	p	Significant difference
Departments	Between Groups	.042	2	.021	4.497	.015	ST-RCR
	Within Groups	.286	61	.005			
	Total	.328	63				
Location of the computer	Between Groups	.018	2	.009	1.791	.175	–
	Within Groups	.314	63	.005			
	Total	.331	65				

Table 2
Changes in sadness according to gender, lecture hours, lecture type and session information.

Variable		n	$\overline{X}$	s	df	t	p
Gender	Female	24	.214	.074	64	1.401	.972
	Male	42	.188	.068			
Lecture hours	Morning	17	.226	.065	62	1.925	.810
	Afternoon	47	.188	.072			
Lecture type	Theory	27	.220	.077	64	2.172	.227
	Practice	39	.185	.063			
Session information	1. Session	41	.204	.0714	64	.926	.656
	2. Session	25	.187	.0715			

According to Fig. 5 and 32 students' feelings of happiness, contempt and fear increased from the first stage to the third stage of the lecture, while anger decreased sharply and sadness increased at first and then started to decrease. There was no significant change in the feelings of confusion and disgust. Table 3 involves the results of repeated measures ANOVA analysis to determine whether the observed changes were significant.

The result of the analysis shown in Table 3 illustrated that there was a significant difference in the change of contempt, anger, happiness and sadness according to the stages of the lecture.

The study revealed that the students' feeling of **contempt** differed according to the lecture stages ($F (2,62) = 1.172$, $p < 0.05$). The mean score ($x = .0497$) in the first stage of the lecture was lower than the mean score in the second stage ($x = .0673$), and it is evident that this difference was statistically significant. The study indicated that there was a significant difference in the feeling of **anger** according to the stages of the lecture ($F (2,62) = 1.172$, $p < 0.05$). It was determined that the significant difference occurred between the 2nd and 3rd stages of the lecture and the mean value of anger during the 2nd stage ($x = .0371$) was lower than the mean value of anger during the 2nd stage ($X = .0543$). As shown in Fig. 5, **happiness** saw a constant rise from the first stage to the last stage. According to the results of the analysis, the difference was significant ($F (2.62) = 10.142$, $p < 0.05$), and while the mean value was $x = .1210$ in the first stage, it increased in the second stage ($x = .1827$) and also in the last stage ($x = .2599$). It was determined that there was a significant difference in every stage. The change in the feeling of **sadness** was found to be significant in the first and second stages of the lecture ($F (2,62) = 9.129$, $p < 0.05$). The mean value of sadness during the 1st stage ($x = .1517$) was lower than the mean value in the 2nd stage ($x = .2213$).

4. Conclusion and discussion

In this study, we analyzed the facial expressions of 67 students studying Journalism, Recreation, Science Teaching and Basic Information Technologies during the theory- and practice-based lectures. Disgust, sadness, happiness, fear, contempt, anger and surprise are universally accepted emotions (Ekman & Friesen, 1976). In the study, these emotions in the facial expressions of the students were converted to digital data by means of a software developed using Microsoft Emotion Recognition API and C # language. With the digital data collected, we examined how students' emotions changed, how they changed according to their departments, gender,

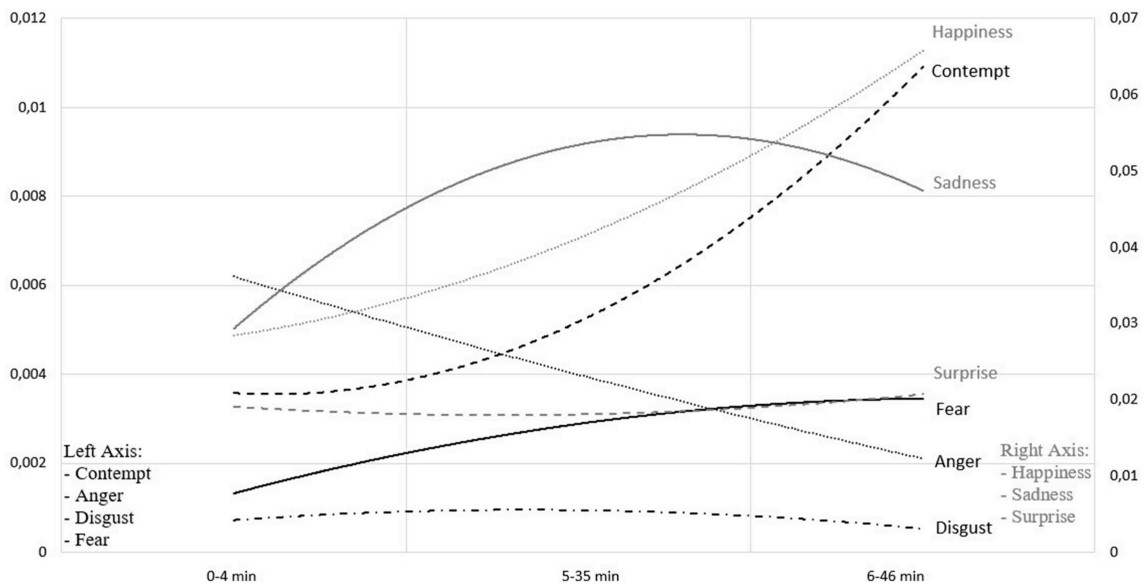

Fig. 5. The change in the emotions of the students according to the stages of the lecture.

Table 3
The change in emotions according to the 1st, 2nd and 3rd stages of the lecture.

Emotion	Source of variance	Sum of squares	df	Mean squares	F	p	Significant difference
Contempt	Between subject	.167	31	.325	1.172	.000	1–2
	Measure	.005	2	.003			
	Error	.133	62	.002			
	Total	.305	95				
Anger	Between subject	.090	31	.003	4.664	.022	2–3
	Measure	.008	2	.004			
	Error	.053	62	.001			
	Total	.151	95				
Happiness	Between subject	.717	31	.023	10.142	.001	1–2
	Measure	.310	2	.194			1–3
	Error	.947	62	.015			2–3
	Total	1.974	95				
Sadness	Between subject	.344	31	.011	9.129	.001	1–2
	Measure	.067	2	.034			
	Error	.228	62	.004			
	Total	.639	95				

lecture hours, the location of the computer in the classroom, lecture hours and session information, whether the differences in the emotions were significant according to the three different stages of the lecture, and the relationship between the changes in emotions and achievement. As a result of this examination, it was evident that while the feelings of contempt, anger, fear and confusion increased in the first 4 min of the lecture, the feelings of happiness, sadness and disgust decreased. If an educator activates the student's willingness in the first few minutes of the lecture, having a motivated student is likely to increase (Keller & Burkman, 1993). Therefore, it can be argued that the lecturer should employ more activities to stimulate the students' willingness in order to increase the motivation of the students. It was determined that happiness increased rapidly while all other emotions fell rapidly at the closure section of the lecture. In their study where they measured 12 lectures of 4 different instructors consisting of 50 min at 5-min intervals, Stuart and Rutherford (1978) found that the concentration level of the students was highest in the first 10–15 min of the lecture. Another similar study revealed that, among the three feelings which are considered to be related with the level of concentration, contempt declined rapidly, while happiness and confusion increased in the first 10–15 min. Frost (1965) stated that all participants were distracted after 35 min (cited by: Wilson & Korn, 2007). Our study revealed that approximately after the 35th minute disgust, confusion, anger, fear, sadness and contempt decreased, while happiness increased. According to the observations of the lecturer, after the 35th minute, the students' attention in the lecture decreased and the feeling of happiness increased because the students realized that it was the last stage of the lecture.

The study showed that the emotions of the students during the lecture did not see a significant difference according to their departments, gender, lecture hours, the location of the computers in the classroom, lecture type, and session information, and also indicated that only sadness was experienced more intensively by Science Teaching students than Recreation students. The instructor believes that this could have been due to the profiles of the students.

In the first part of the lecture (0-4th minute), the lecturer gave some general information about the lesson. It is considered that the information given about the subject caused a decrease in the feeling of anger rapidly, an increase in the feeling of happiness, and also the formation of fear. In the second stage of the lecture where the content of the lecture was explained, the feeling of sadness increased slightly at first. This rise was felt by the lecturer. Bunce, Flens, and Neiles (2010) stated that, asking questions and practicing can prevent distraction, whereas Bligh (2000) suggested that using various motivational methods such as clarity in the subject, enthusiasm and drama can have the same effect. For this reason, the lecturer used a variety of motivational activities in the study (jokes, changing the subject, asking questions, using multimedia elements) which were thought to be able to reduce the negative emotions in students. As a result, the feelings of sadness, anger and disgust decreased, while the feelings of happiness increased. The amount of concentrated time is affected by whether the task one must focus on is attractive, entertaining, and practice-based, as well as such factors as fatigue, hunger, noise and emotional stress. Considering these factors, the attention span for adults is about 20 min (Cornish & Dukette, 2009). This study revealed that there was a decrease in the feelings of contempt, sadness, fear, disgust and an increase in happiness after approximately 20 min. This is thought to be caused by the activities employed by the instructor. It was found that, in the last stage of the lecture (36th-46th minutes), happiness and contempt increased much faster than in the other stages, and there was a rapid decrease in the feeling of sadness and anger, while there was no significant change in the feelings of disgust, fear and confusion.

In line with the study, it is suggested that each lesson in the education process be considered as a mini presentation, and that instructors, as if they were performing an effective presentation, employ various methods during the lecture such as giving short breaks frequently, allowing interaction, asking questions, moving around the classroom, changing the subject, and telling a story. It is also advisable that the equipment that monitors students' emotions should become widespread in educational institutions and the instructor can be provided with feedback thanks to data collected by this equipment. In future studies, emotions can be analyzed in different lectures, different departments and age groups. Further data about the emotions to be collected can be examined by considering various variables in the educational environment. In addition, the effect of each emotional change on the key factors of learning can be examined.

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