Online Classroom Evaluation System Based on Multi-Reaction Estimation

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ABSTRACT

Online learning is more convenient than traditional face-to-face teaching methods. However, during real-time online classes, it is difficult for teachers to observe the reactions of all students simultaneously. Herein, we introduce an online education classroom evaluation system that enables teachers to adjust the speed of their lessons based on students' reactions. We aim to develop a method that can evaluate student participation based on multi-reaction of students. In this study, the system estimates the head poses and facial expressions of students through the camera and uses the information as criteria for assessing student participation. The estimated result enables the class quality to be categorized into positive, negative, and neutral, thereby allowing teachers to rearrange the class contents. Finally, we evaluate the performance of our system by testing the accuracy of student reaction estimation and our classroom evaluation method.

CCS CONCEPTS

• Applied computing → Computer-assisted instruction.

KEYWORDS

Online classroom, Classroom evaluation, Human behavior detection, Head pose, Facial expression recognition

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1 INTRODUCTION

Online education is a new mode of distance education that began in the mid-1990s and emerged with the development of the Internet. Online education has become increasingly highlighted due to its advantages: it transcends the limitations of time and space, and it can mitigate the unequal distribution of educational resources due

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to geography and other aspects. However, student performance is an independent aspect in any kind of classroom, it is difficult for a teacher to observe each student's classroom reaction. Moreover, students' reactions in the classroom are not monolithic; they are a combination of head poses, body movements, and facial expressions. This problem is more prominent in online classrooms. In an online classroom, the teacher must observe the students' performance from a camera individually to determine the current feedback of the students. However, for an online classroom with 30 students, this problem renders it more difficult for teachers to gauge the students' reactions in a timely manner and causes the teachers to lose focus on the class content. Moreover, this problem is exacerbated by the multiple reactions of students.

In most current online education systems, teachers can observe their students' class reactions through cameras; however, this distracts the teacher from the lesson and requires a significant amount of time to observe students' reactions individually. To evaluate the overall classroom quality based on the reaction estimation of all students without affecting the attention of students and teachers, we developed a new online classroom supporting system, that can evaluate student participation based on students' multi-reaction.

The remainder of this paper is organized as follows: Section 2 introduces studies related to student multi-reaction estimation, namely, the detection of students' head poses and facial expression. Section 3 describes the process by which an online classroom platform is constructed. Section 4 presents the method used to estimate students' multi-reactions in this study, as well as the effect of students' reactions on classroom evaluation. In Section 5, a new online classroom evaluation method based on students' multi-reactions is presented. In Section 6, the feasibility of the proposed classroom evaluation method based on experiments is presented, and the works are discussed. Finally, the conclusions are provided in Section 7.

2 RELATED WORK

2.1 Head Pose Estimation

Humans use their head orientation to convey information during interpersonal interactions, for example, a listener nods to a speaker to indicate that he/she understands the information being communicated, or a listener pulls his/her head back to indicate avoidance or disapproval. Li [6] proposed a method that estimates the attention of 30 students in a class using a camera that real-time detects their head rotation without recognizing the eyeball pose; subsequently, they visualized the three states of student learning. Xu [11] proposed a multiple Euler angle constraint method to create a

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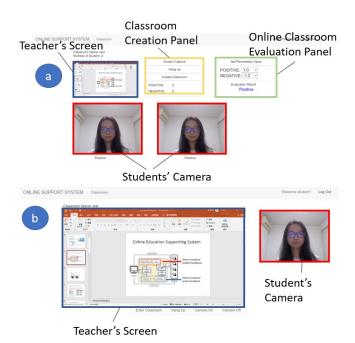


Figure 1: Interface of online classroom system. (a) Teacher page interface containing local stream of teacher's screen, students' camera streams transmitted by WebRTC, classroom creation panel, and online classroom panel. (b) Student page interface containing student's local camera stream and teacher's shared screen transmitted from teacher's page by WebRTC.

scoring module to analyze students' attention based on head pose estimation, where the system reported evaluates student attention levels from 0.0 to 1.0.

Based on the studies above, it can be concluded that by detecting students' head poses, the current class participation of students can be inferred effectively. This study focused on detecting each student's nodding and shaking head poses during class via a camera. As only one student is visualized in each camera, a multi-target situation does not apply; hence, estimation errors are effectively reduced.

2.2 Facial Expression Recognition

In addition to head orientation, human expressions convey a significant amount of information and emotional states during interpersonal communication. Ekman et al. [3] defined six basic human expressions and indicated that humans convey the same emotional message for basic expressions regardless of culture and region. The six basic facial expressions are anger, disgust, fear, happiness, sadness, and surprise. In the fields of deep learning and computer vision, various facial expression recognition (FER) systems exist that extract expression information from facial representations. With the development of deep learning theory and improvement in numerical computing equipment, CNN has been rapidly developed and widely used in computer vision and other fields. Currently, some well-known CNN structures are being applied to expression

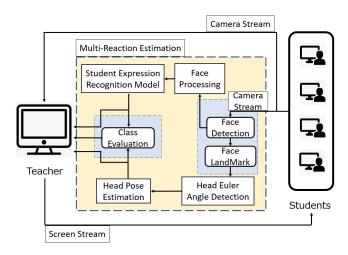


Figure 2: Structure of online classroom system

recognition, such as VGGNet [10], which is used to extract image features owing to its brief structure and excellent versatility.

However, in regard to student expressions in the classroom environment, the abovementioned criteria for classifying expressions are inappropriate. Liang[7] classified students' expressions into four categories: interest, happiness, confusion, and tired according to the classroom environment; and automatically recognized facial expressions using a support vector machine. However, this study still suffered from a small dataset sample and a single scenario.

3 ONLINE EDUCATION PLATFORM

To provide a platform for teachers and students to conduct online learning activity, we developed a simple online classroom system.

3.1 Real-time Communication Channel

Our system is based on WebRTC and sockets for peer-to-peer video streaming transmission, which can achieve real-time communication through JavaScript provided by browsers. To perform educational tasks, the system enables the teacher and students to share the teacher's screen and capture students' web cameras in an online classroom.

The system allows multiple classrooms to be created based on the teachers' needs, and teachers can create a classroom in the classroom creation panel, as shown in Figure 1-a. The different classrooms are independent of each other, which allows students to enter the classroom by inputting their names. When the student enters the classroom, the student's socket ID is sent to the teacher and recorded by the teacher. In the subsequent student reaction estimation, the system distinguishes each student's detected result using this socket ID. After the teacher page receives the socket ID from the student page, the teacher and student's page channels are linked. When the channel is connected, the screen shared by the teacher is displayed on the student pages; the interface of the student page is shown in Figure 1-b. On the teacher page, the teacher can observe the students' reactions in class through a video transmitted from the students' cameras. Furthermore, the teacher

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can verify the students' responses and the overall class evaluation from the online classroom evaluation panel.

3.2 Online Classroom System

We show the overall structure of our online classroom system in Figure 2. First, as described in Section 3.1, the teacher and student pages transmit the streams of the teacher-shared page and students' videos through WebRTC and sockets. In addition, the student camera video stream is transmitted to the multi-reaction estimation module to determine the student's learning status based on the student's head and facial information. The student's learning status can be determined using one of two approaches: head pose estimation and expression recognition.For head pose estimation, by detecting the face in the camera video stream, face landmarks are obtained, and then the head Euler angle is calculated based on the face landmark to determine the head pose. For expression recognition, the student's face region is preprocessed after the face region in the camera video stream is detected. The expression recognition model is used to detect the expression of the processed facial region. Additionally, the current student's listening state (positive, negative, or neutral) is assessed based on their head pose and expression.In addition, the students' head poses and expressions are used for classroom quality evaluation, and the overall classroom is evaluated by evaluating the status of all students.

4 MULTI-REACTION ESTIMATION

In any type of classroom, both the teacher and students significantly affect classroom performance. Students respond to the teacher's course content correspondingly, and the teacher can adjust the speed of the course based on the students' reactions. In this study, we classified students' reactions into positive and negative reactions. Students with no feedback regarding the class are considered neutral.

4.1 Student Head Reaction

Our system assumes that students nod to indicate that they understand the teacher's explanation, and that they shake their heads otherwise. The system estimates the students' head poses based on their face landmarks. Therefore, to improve the accuracy of head pose estimation, students should position their heads in the middle of the video camera area.

To estimate the head pose, the system is required to detect faces in video streams transmitted from the students. We used the Tiny Face Detector [4] as an implement to detect students' faces in the video stream. For each detected face, we can obtain 68 key points called face landmarks, and store them in a container of points. The front-end sends the students' face landmarks to the server every 100ms.

Head pose estimation is conducted by obtaining the pose angle of the head from the face landmark. In a 3D space, the rotation of an object can be represented by three Euler angles: the pitch, yaw, and roll. To solve the transformation relationship between 2D facial key points and a 3D face, a 3D face model must be developed. In our system, we used a 3D model under normal circumstances. To convey 2D information, we used 14 face landmarks to create a twodimensional model. The solvePnP function provided by OpenCV can calculate the rotation vector and translation vector based on two-dimensional facial key points, a 3D face model, as well as the camera matrix and camera distortion. The values of pitch, yaw, and roll can be calculated from the rotation vector; subsequently, a simple tracking method can be used to estimate the students' head pose.

Our system estimates the head pose based on the tracking method which detects the head between consecutive frames of a video stream. Additionally, the head pose is initialized with a frontal face to improve the accuracy of head pose estimation based on a frontal face. Therefore, we required the students to position their heads in the middle of the video camera. The general range of motion of the human head are +60 to -60 degrees of pitch angle, and +75 to -75 degrees of yaw angle. The research of Chen [1] demonstrated that the average duration of head movements is 850ms. Therefore, we used the following approach for head-pose estimation in the ordinary case: (1) Every 100ms, we calculate the Euler angle of the students' head poses. (2) When the pitch angle of two adjacent detections is greater than 10 degrees, we assume that the student nodded. (3) When the yaw angle of two adjacent detections is greater than 12 degrees, we assume that the student shook his/her head.

4.2 Student Expression Reaction

In Section 4.1, we presented a method to estimate students' head poses based on facial landmarks; this method can effectively help teachers assess the current students' understanding of the course content. However, the estimation of head poses requires students' active feedback; this implies that if students do not actively provide feedback regarding the classroom content, then our system is not able to support the teachers' evaluation of the classroom. Therefore, we propose the detection of students' implicit feedback regarding classroom content based on student expressions.

As mentioned in Section 2.2, the classification of the six basic expressions (anger, disgust, fear, happiness, sadness, and surprise) cannot be applied simply to the educational environment. In this study, we primarily categorized classroom expressions into happiness, focused, confused, disgust, and tired based on the students' emotions in the classroom. Finally, we defined the students who had no expression changes as neutral.

Most existing expression recognition datasets are based on six basic expressions for classification. To create a suitable dataset for recognizing classroom expressions, we obtained expressions in the following two categories: For part A, which is associated with basic expressions of happy, disgust, and neutral, we selected expression samples from the existing datasets; for part B, which is not associated with basic expressions of focused, confused, and tired, we obtained samples from Google images.

In this study, we selected happiness, disgust, and neutral samples from three datasets: JAFFE[9], CK+[8], and SFEW 2.0[2]. Among them, JAFFE and CK+ are laboratory-controlled samples, whereas SFEW 2.0 is intercepted from the actors' expressions in the movie clips. Because CK+ is a sequence dataset, we extracted the last frame with peak formation and the first three frames (for neutral face) of each sequence. For samples in part B, we used the following approach to obtain the expression samples: First, we collected images of keywords through the Selenium API; next, we filtered WI-IAT '21, December 14-17, 2021, ESSENDON, VIC, Australia



Figure 3: Examples of datasets used for student expression recognition. In these examples, focused, confused, and tired samples from Google image. Happiness and disgust samples from SFEW 2.0. Neutral sample from JAFFE.

Feature Extractor					Classifier				
Input Data	Conv. 5×5 64	Conv. 5×5 64	Max Pooling 2×2	Conv. 5×5 64	Conv. 5×5 64	Max Pooling 2×2	64	Fully Connected 64	Softmax
	ReLU	ReLU		ReLU	ReLU		Dropout 0.6	Dropout 0.6	

Figure 4: The architecture of CNN model

non-face images using the Tiny Face Detector. Finally, we manually selected images that did not match the keywords (confusion expression, focused expression sleepy, and sleepy expression) or education environment. For example, we removed some exaggerated expressions and some images with too many facial obscurations.

The dataset of student expressions in the classroom that we collected is shown in Table 1. After organizing the dataset, we cropped the face region and performed grayscale processing; finally, the sample image was resized to 48×48 . Figure 3 shows an example of each expression after pre-processing. Similar to the evaluation benchmark of student reactions presented in Section 4.1, we reclassified the student expression dataset as positive, negative, or neutral. Among them, happiness and focused were positive reactions; disgust, confused, and tired were negative reactions.

The CNN structure that we constructed based on ours frame [5], which contains four convolution layers with two additional fullyconnected layers at the end of the network and a ReLU were used for each convolution layer as an activation function. The Figure 4 shows the architecture of our CNN model.

5 ONLINE CLASSROOM EVALUATION

In our system, class evaluation is based on the students' reaction estimation. After the system estimates the students' head poses and expression reactions, the system collects the head poses and the expression reactions of all students in the classroom to evaluate the current classroom participation. During class, we assume that a) the class content is related before and after, and b) some students are not attentive. For those cases, we assume that when the student does not understand the previous content of the course, it is more difficult for him/her to understand the current explanations of the teacher as compared with other students. For our evaluation method, we assume that students with good performance participation are more important in the classroom. Therefore, we increase Table 1: Our dataset of student expression for classroom expression recognition, it contains 1,089 training set and 281 testing set.

Category	Samples	Train	Test	Total
Happiness	216	170	46	
Focused	85	68	17	
Confused	134	106	28	1370
Disgust	130	101	29	1370
Tired	96	76	20	
Neutral	709	568	141	

the effect of positive reactions on the class evaluation when considering the class evaluation method. To reduce interference in the two abovementioned cases, a weighted method is used in the system to calculate the overall listening of the students.

As mentioned in Section 4, we regard students' nodding heads, happiness, and focused as positive reactions; and shaking head, disgust, confused and tired as negative reactions. We evaluate the quality of the class r_{class} using the following method:

$$r_{class} = \sum_{i=1}^{n} w_i r_i \tag{1}$$

Where r_i and w_i are the reaction and weight of student s_i , respectively. r_{class} shows the value of a class reaction considering $r_1, r_2, r_3, ..., r_n$.

We consider that when the majority of students in the classroom are positive, the current classroom evaluation result is positive, on the contrary, we consider the classroom as negative if negative students are the majority of the classroom. Therefore, when r_{class} is greater than or equal to 0.2, the current classroom level is considered positive. When the r_{class} is less than -0.15, the current classroom level is considered as negative. When the r_{class} is -0.15 to 0.2, the current classroom level is neutral. For cases mentioned above, the method evaluates the current class reaction by considering both students' past performance and current reaction. This method can reduce the effects of students who have not participated in the past on the current classroom evaluation. The classroom evaluation method is suitable for small classes comprising 30 students or less.

Here, we show an example of POSITIVE result on the teacher page in Figure 5. To define the value of r_i , we set 1 for positive reactions, -1.2 for negative reactions, and 0 for neutral. We defined the positive and the negative reactions with unequal values because in a classroom, teachers should conduct classroom activities that enable students to understand the content of the lesson; therefore, we assigned a higher negative value to negative reactions.

For weight of each student, we define the value of w_i as follows:

$$w_i = \frac{f_i}{\sum_{j=1}^n f_j} \tag{2}$$

This weight calculation algorithm reduces the weight coefficient f_i proportion of student s_i as the number of students increases. When the number of students in the classroom is sufficiently large, the weight coefficient f_i proportion of student s_i approaches 0.

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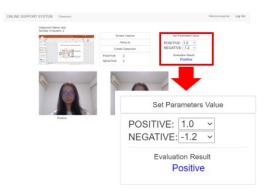


Figure 5: An example of POSITIVE Result on the teacher page

Therefore, we specify less than 30 students in the classroom when using this method to assess classroom level.

Then, count the number of negative reactions n_i and the number of positive reactions p_i of the student s_i from the beginning to the positive moment. In addition, we considered the effect of the number of student reactions on the classroom evaluation function. Therefore, we used a logarithmic function to reduce the effect of the students' reaction times.

The weight coefficient f_i of student s_i is expressed as

$$f_i = \log\left(2p_i + n_i\right) \tag{3}$$

We use the logarithmic function to reduce the effects of students' past reaction times on the weight coefficient, where p_i is twice of n_i . This is because we assume that in past reactions, students with more positive reactions can better understand the content taught by the teacher, and hence it is relatively easy for them to understand the current class content. As such, the coefficient of positive reaction p has a higher weighting than the negative reaction n.

6 EVALUATION AND DISCUSSION

To assess the performance of our online classroom support system, we firstly evaluated our head pose estimation and student expression recognition model, and the test results were used to verify the class evaluation method proposed in Section 5.

6.1 Evaluation of Reaction Estimation

We evaluated our head pose estimation experimentally. We performed 30 discontinuous head nodding and 30 discontinuous head shaking on the student's page, and the experimental results obtained on the teacher page are shown in Table 2. In the 30- nodding-head tests, 25 were correctly predicted as nodding, 3 were predicted as shaking, and 2 were neutral; the accuracy of the nodding test was 0.83. Meanwhile, in the 30-shaking-head tests, 24 were correctly predicted as shaking, 5 were predicted as nodding, and 1 was neutral; the accuracy of the shaking test was 0.80.

Next, we describe our experiment using the proposed expression recognition model. The dataset mentioned in Section 4.2 was categorized into a training set and a testing set, and they contained 1,089 and 281 samples, respectively. We trained our expression recognition model using the dataset obtained, and the experimental Table 2: Experimental result of head pose estimation

Action Result	Nodding Head	Shaking Head
Nodding Head	25	5
Shaking Head	3	24
Neutral	2	1
Accuracy	0.83	0.80

Table 3: Experimental result of expression recognition model

Input Result	Negative	Positive	Neutral
Negative	60	6	11
Positive	19	38	6
Neutral	5	5	131
Accuracy	0.71	0.79	0.89

results are shown in Table 3. This experiment involved 84 negative samples, 49 positive samples, and 148 neutral samples. For the negative, positive, and neutral samples, the final accuracies of the model were 0.71, 0.79, and 0.89, respectively.

6.2 Classroom Evaluation

Based on the experimental result of student reaction estimation, we used the method mentioned previously to evaluate the class as a whole. Because the number of students in the classroom, such as 10, 22, or 30 students, as well as the reaction of students can affect the classroom evaluation results, we assumed a classroom of 30 students, and that the number of students' previous state reaction was between 6 and 12 times. Among them, 16 students had more positive than negative reactions, 10 students had more negative than positive reactions. Next, considering the students' current reactions, we changed the classroom evaluation r_{class} by adjusting the students' current reactions. To evaluate the classroom, we used the test results presented in Section 6.1, and assumed that the probability of students performing head pose reaction and expression reaction was equal.

By randomly adjusting each student's current reaction state (positive, negative, and neutral), we tested the true r_{class} from -1.2 to 1 for each case with a step size of approximately 0.1, and each case was tested 1,000 times to obtain the average r_{class} and the classroom level prediction; the results are shown in Figure 6. As an example, when all students were positive, the true r_{class} is 1. However, as presented in Section 6.1, the system's estimation of student reactions differ from the real student reaction, and our classification of the overall classroom level, the r_{class} of these 1,000 tests were all positive; therefore, we assumed that the accuracy of the proposed method was 100% in evaluating the toward the zero as compared with the true r_{class} deviated significantly from the true r_{class} , and the maximum deviation value was 0.509. When the true r_{class} was approximate to zero, the test r_{class} did not deviate

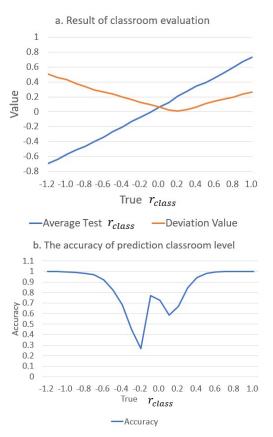


Figure 6: (a) Result of classroom evaluation. (b) Accuracy of classroom level prediction.

significantly from the true r_{class} , and the minimum deviation value was 0.007. In addition, the accuracy of our proposed method for evaluating the classroom was high when the true value was far from the discriminant value (0.2 and -0.15), and the highest accuracy was 1. By contrast, when the true value was approximately the discriminant value, the accuracy of the method for evaluating the classroom was low, with the lowest accuracy of 0.267. The average accuracy of the proposed method was 0.852. Considering another situation where the weight w_i of students is not affected by previous behavior, that is, the weight between students is equal, we got the following results, the average accuracy of no weight situation is 0.842, it is lower than the method we proposed.

6.3 Discussion

For student reaction estimation, the estimation accuracy of our system is to be improved. For head pose estimation, the system requires students to position their heads in the middle of the camera, and the system cannot easily detect head rotations that are extremely subtle. Regarding the laboratory-controlled facial expression datasets we used for student expression recognition, some of the facial expressions were exaggerated and did not match the students' facial expressions in the classroom environment. In addition, the methods for estimating head poses and facial expressions have high requirements for the background and illumination of the image captured by the camera. In future studies, the abovementioned aspects should be improved, and evaluation experiments should be strengthened by using real videos of students in a class.

7 CONCLUSION

A new method for assessing student participation through head pose estimation and expression recognition was proposed herein; in this method, the current classroom is evaluated based on students' reactions. This study focused on the classroom evaluation method, and experimental results showed that the proposed method can effectively evaluate the overall listening of students with an accuracy of 85.2%, even though the reaction estimation for a few students was inaccurate. Therefore, the system can support teachers in providing better teaching activities and evaluating small online classes.

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