Quantitative Analysis of Facial Expression Recognition in Classroom Teaching Based on FACS and KNN Classification Algorithm

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Abstract. Facial expressions are an important information carrier for individuals to communicate emotionally in the educational system. Through the communication of expressions, teachers and learners can perceive each other's emotional changes. Learners will unconsciously convey personal thoughts and feelings through facial expressions, and can also identify the attitude and inner world of the other party by observing facial expressions. Expression contains rich behavioural information and is the main way of emotional transmission. As an important direction of individual learning behaviour analysis, facial expression recognition constitutes the basis of emotion understanding and is the premise for computers to understand learners' emotions. This paper mainly uses the camera in front of the classroom to record the high-definition video of classroom teaching. From the sampled frame images, the AdaBoost algorithm is used to locate and intercept the faces of all students in the classroom, and the images are pre-processed to obtain a 64 × 64 pixel expression area. Gabor and ULBPHS feature fusion, after PCA+dimensionality reduction, combined with KNN classification method for expression classification. Finally, the judgment and output of learning emotions are realized.

Keywords: Classroom Teaching · FACS · Adaboost Algorithm · KNN Classification Method · Quantitative Analysis

1 Introduction

American psychologist Albert. Mehrabian (Albert Mehrabian) believes that emotional expression = 7% of words+38% of tones+55% of facial expressions and actions [5]. The types of expressions concerned in the learning scene are different from the six basic types of expressions used in the general human-computer interaction, and more attention is paid to the cognitive and emotional state of the students in the learning scene [6]. In learning scenarios, expressions such as engagement, boredom, confusion, curiosity, happiness, and frustration appear more frequently, while expressions such as contempt, anger (anger, disgust, sadness, anxiety, delight, fear, and surprise appeared less frequently in learning scenarios [7].

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Ivon Arroyo et al. tracked the expressions of high school students and college math students who collected data in a multimodal manner during the experiment, including interaction data, facial features, posture, skin conductance, mouse move etc. [9]. Based on the self-labeled labels of the subjects, their experimental results show that the emotional state can be automatically detected in the classroom environment, but their model has not been verified, and the amount of data is insufficient due to missing data overlearning behavior [4]. In order to avoid the problem of expression recognition learning, Nigel Bosch et al. selected 137 (57 boys and 80 girls) 8th and 9th grade students, and these subjects were divided into about 20 students. Group, 4 stages of experiment were carried out, and the time of each stage was maintained at 55 min [3].

Scholars such as Grafsgaard of North Carolina State University tracked learners' facial expressions during online learning to identify whether their emotional states were expressive frustration or active engagement [2]. The benchmark data of the study was designed with 67 American college students who volunteered to participate in the experiment, with an average age of 18.5 years. They participated in the 2011–2012 school year introductory computer online course, a total of 6 classes. In particular, the experiment does not require participants to have prior knowledge of computer science, and the learning platform provides learning tasks, computer programming interfaces, and text dialogs [1]. All students' facial expressions during the learning process are recorded by armament cameras and formed into video files. A large number of facial action units are tracked frame-by-frame using the Computer Expression Recognition Toolbox (CERT) (Littlewort 2011). In a video frame, CERT first identifies a face, localizes the features most similar to the target face, including eyebrows, eyelids, and corners of the mouth, and uses a support vector machine to calculate the weight of each facial action unit it tracks. The method of profiling facial expressions is: (1) output the average value of each facial action unit of each student, these values correspond to the individual baselines of facial expressions; (2) extract each type of facial action unit in each class process. The average value in, forms the individual-based CERT output data, and a positive result indicates that CERT has identified an action unit, where an empirical threshold of 0.25 is used to adjust the data set to reduce the false detection rate, and then the adjusted data set is used to Represents the state of facial expression; (3) Build a prediction model, use a stepwise linear regression model based on the minimum Bayesian information criterion to train each action unit, and the feature variables involved in the prediction model include eyebrows, eyelids and mouth corners coordinates, eyebrows The number and intensity of uplift, the number and intensity of eyebrow tail uplift, the number and intensity of eyebrow drop, the number and intensity of closed eyes, and the number and intensity of mouth sunken [8].

The experimental results show that the frequency and intensity of facial movement have certain predictive effects, and several conclusions are drawn.

(1) Intensity features can distinguish emotional states involving similar actions, such as anxiety and confusion in the frustration category, which can be effectively identified by measuring the level of intensity feature values.
(2) In the analysis of the predictive ability of different features, it was found that the intensity of eyebrow lowering was positively correlated with frustration and the determination to give up future courses; learning tolerance was negatively correlated

with the intensity of eyebrow lowering, and positively correlated with the intensity of eyebrow raising; the frequency of eyebrow raising was correlated with The time length of learner demand is negatively correlated; the frequency of mouth corners is positively correlated with learning performance, and students who frequently make mouth corners inward tend to perform better in learning; finally, the strength of eyebrow uplifting and the frequency of mouth corners are measured. It was found that the gain of learning effect was negatively correlated with the strength of the eyebrow raising, and positively correlated with the concave corner of the mouth.

(3) The researchers believe that the high intensity of facial movement may imply that the learner's internal emotional arousal is higher, and this intensity information is helpful to diagnose the emotional state of low arousal.

2 Features of Facial Expression Recognition in Classroom Teaching

When learning facial expression recognition for students in the classroom teaching process, the following issues need to be paid attention to.

(1) Learning expression classification. Existing research on expression recognition corresponds to 6 discrete expressions (anger, disgust, fear, happiness, sadness, surprise) classified by Ekman. To identify, no significant research results have emerged. By watching a large number of past teaching videos, we found that: in the course of classroom teaching, when students are curious, they will appear surprised expressions, when they enjoy teacher praise and classmates envy, they will appear happy-happy expressions, other discrete expressions (sadness, fear, anger, disgust) generally do not appear. In fact, the two discrete expressions of surprise and happiness are less likely to appear, and the more likely to appear is the frowning expression of thinking. Therefore, it is necessary to construct a new learning expression classification system according to the needs of classroom evaluation.

(2) How to improve the expression recognition rate of low-resolution faces. The classroom area is large. For a classroom with a depth of 10 m, even if a 4K camera is used to shoot the faces of the students in the last row, the pixels in the expression area are relatively low. Some expression recognition algorithms based on deep learning technology need to be used to improve expression recognition. Rate.

(3) Parallel acceleration of expression recognition. The automatic evaluation of classroom teaching needs to identify the expressions of all students in the classroom. For the discrete frame images of the teaching video, after detecting the faces of all students, parallel expression recognition can be performed on the face images of these students to speed up expression recognition. It can improve the practicability of automatic evaluation of classroom teaching.

(4) Restrict the use of facial expression recognition. In the classroom teaching process, in the teaching scenarios where students' faces cannot be obtained in large numbers, such as practice and note-taking, the analysis tool of facial expression recognition will not be used. It is only necessary for teachers to teach and show Expression recognition is required only in the teaching scene where students look up to listen to the class. However, after face detection, head posture detection must be used to

exclude faces with large head posture swings, and perform expression recognition on faces with qualified head postures to reduce the workload of form recognition and improve expression recognition rate.

In the current educational environment, learners can only understand their learning effects through academic performance evaluations or other written evaluations given by teachers, lacking in-depth understanding of their own physiology or psychology, and unable to correctly understand their own learning (Xing 2016). Learning habits after points of interest. It is difficult for the tested students to clearly and intuitively understand their own learning situation during the learning process. Therefore, when learning problems occur, they are often unable to accurately focus on the root of the problem, or cannot accurately understand the root of the problem. For example, when some of the tested students have unsatisfactory academic performance due to lack of concentration, the individual tested students may not be aware of the problem of distraction. Therefore, the test students need tools to help them improve their self-assessment, and use data facts to help the test students understand their personal study habits. Through the inquiry of personal data, establish self-awareness and evaluation of personal learning attitude and other aspects, understand their own learning situation, conduct self-reflection, and actively adjust during the class process, form good study habits, and improve learning efficiency (Huber 2016).

For teachers, although it is possible to make subjective judgments on students' classroom performance through the accumulation of senior teaching experience, this method is very dependent on teachers' teaching experience. Experienced backbone teachers may make more accurate judgments, but young teachers lack experience due to their lack of experience, there are certain difficulties in judging students' classroom performance [9]. At the same time, although many schools are currently developing the "small class teaching model", there is still a one-to-many phenomenon for classroom teaching. It is difficult for teachers to pay attention to each student's learning in the classroom. Therefore, the original analysis is insufficient and the empirical approach has certain limitations. It is important for teachers to fully and properly mobilize learners' attention. Only by mastering the characteristics of learners' attention can we more effectively grasp the situation of each learner, better organize the teaching content, and optimize the teaching strategy.

When the tested students are studying in the classroom, the computer can monitor the learners' current head posture in real time through technical means, and analyze the data of their attention. Complete the attention analysis of the student based on the attention situation data. At the same time, the collection of data should be completed without affecting classroom teaching, so as to ensure the non-perceptual, full-process, and fully automatic implementation of the analysis process.

3 Basic Knowledge of Facial Expression Recognition

Changes in facial muscles can produce changes in facial expressions, that is, the combination of changes in a person's eyes, lips, eyelids, and eyebrows can produce different expressions. American psychologists Paul Ekman and Wallace V. Friesen did pioneering work on facial expression recognition in the 1970s. By summarizing the facial expression assessment work, they developed a comprehensive system to distinguish facial movements as much as possible, namely the Facial Action Coding System (FACS). Paul Eikman divided the face into 46 motion units (Action). Unit, AU), descriptions and picture examples of some motion units are shown in Table 1 (Table 2).

Table 1. Facial motor units

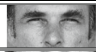
Motion Unit	Description	Instance	Motion Unit	Description	Instance
AU1	Brow Lift		AU2	External Eyebrow Lift	
AU4	Eyebrows Drooping		AU5	Lift The Upper Eyelid	
AU6	Lift Cheeks		AU7	Eye Retraction	
AU9	Wrinkled Nose		AU10	Lift Upper Lip	
AU11	Deepen The Middle Nasolabial		AU12	Pull The Corners Of The Mouth To Tilt Upwards	
AU13	Pull The Corners Of The Mouth Up		AU14	The Corners Of The Mouth Retract Towards The Teeth	
AU15	Pull The Corners Of The Mouth Down		AU16	Lower Lip Pulled Down	
AU17	Squeeze The Lower Lip Up		AU18	Wrinkle The Mouth In The Middle	
AU20	Lips Pulled Back		AU22	Pursed Lips Into A Funnel	
AU23	Tighten Your Lips Into One Word		AU24	Squeeze Lips Together	
AU25	Lips Separated To Expose Teeth		AU26	Lips Parted To See Tongue	
AU27	Lips Parted To See Throat		AU28	Suck Lips To Cover Teeth	

Table 2. Basic expressions of motor unit combinations

Expression	Combination Of Motion Units
Anger	Au4+Au5+Au7+Au15+Au24
Disgust	Au9+Au10+Au17
Fear	Au1+Au2+Au4+Au5+Au7+Au20+Au25
Happy	Au6+Au12+Au25
Sad	Au1+Au4+Au7+Au15+Au17
Surprise	Au1+Au2+Au5+Au25+Au26

4 Quantitative Analysis of Classroom Teaching Process Based on Learning Facial Expression Recognition Technology

By collecting and analyzing relevant literature on learning expressions of listening to lectures, and watching a large number of teaching videos on real classroom teaching, we first roughly divide learning expressions into joy and surprise as shown in Fig. 1 joy (Joy), Surprise (Sur), confusion (Con), focus (Foc), distraction (Dis), and then built a learning expression database dedicated to automatic evaluation of classroom teaching, and finally developed an automatic evaluation of classroom teaching based on learning expression recognition system.

The automatic evaluation system for classroom teaching based on learning facial expression recognition mainly includes the following functional modules.

(1) The frame number image acquisition of classroom teaching video. Use the front camera to record high-definition video of classroom teaching, and discrete a frame of sampling frame image from the video every 2–5 s.
(2) Face detection and localization. From the sampled frame images, the AdaBoost algorithm is used to detect the faces of all students in the classroom, locate and intercept the face images of each student; when a student's head posture offset angle is large, that is, the student's eyes move away from the blackboard When the AdaBoost algorithm will be difficult to detect the face, then the student is defined to give up learning (absent).
(3) Preprocessing of facial expression area. Rotate, crop, and normalize each student's face cut out from the frame image to obtain an expression area of 64×64 pixels.
(4) Expression recognition. Our expression recognition method fuses Gabor features and Uniform Local Binary Pattern Histogram Sequence (ULBPHS) features, and then performs two dimensionality reductions using PCA+Linear Discriminant Analysis (LDA) Finally, the KNN classification method is used for expression classification to solve the problem of low expression recognition rate caused by the low resolution of students' faces in traditional classrooms.
(5) Learning emotion judgment and output. If the face recognition algorithm does not detect a student's face, it is determined that the student has given up learning (absent); otherwise, the expression recognition algorithm is used to discriminate the

Fig. 1. Discrete expressions based on activation and valence (Photo credit: Original)

student's learning emotion, and surprised expressions are used to obtain curious and happy expressions. There are five learning emotional states: mastering knowledge, focusing on learning, concentrating on learning, perplexing, thinking, and distracted expressions, which can automatically judge the learning status of each student.

Through the facial expression recognition of the teachers and students in the whole process of classroom teaching, the learning efficiency of the learners can be monitored in real time, and the teachers can be provided with positive teaching strategy guidance. The analysis results of individual students' facial expression data show that their emotional input in the classroom teaching process is basically in line with expectations. Therefore, it can be explained that the algorithm model has a certain constraint effect and can be further tested. However, it should be noted that the emotional investment of individual learners in the whole course of classroom teaching can reflect that the adjustment of some teaching modes in the teaching process of teachers does not have an obvious "attractive" effect. The most important factor affecting the student's classroom emotional input is time.

At the same time, due to the very lack of the sample size of the subject learning, the data is not unique. However, according to the analysis of the facial expression data of all the tested learners, it can be seen that the emotional engagement of most students in the classroom has a relatively strong convergence. According to the characteristics of college students' high threshold of classroom emotional contagion and small contagion factors, without conducting massive data analysis, it is preliminarily judged that in the course of the subject's classroom teaching, the teacher's teaching strategy design has an impact on the subject learners' learning emotions. Investment has little impact. Especially in the middle of teaching, most of the 10 subjects' classroom emotions were "wandering", and some were "confused", indicating that teachers should adjust teaching strategies in time to improve teaching effects.

After the computer analyzes the classroom emotional input of all the tested learners, it feeds back the classroom emotional analysis results to the teacher through the return headset in real time. After the teachers made positive strategic adjustments, the students' classroom emotions gradually produced feedback, which had an obvious positive effect.

5 Conclusions

Under the premise of incomplete data, this paper initially achieved some results.

(1) Teachers should flexibly prefabricate some measures to accelerate the emotional involvement of students in the classroom, so as to improve the concentration of

all students. For example, the use of pre-class questions, knowledge consolidation, classroom random questions and other means. In the course of class, measures to ease classroom emotions such as teacher-student interaction should also be appropriately increased, so as to relieve students' fatigue in class and relieve students' emotional disengagement before get out of class.

(2) The research results can conduct automatic, full-process, non-perceptual teaching effect evaluation for the classroom teaching process, and can assist teachers in decision-making on teaching strategies. If at a certain moment the students' emotional involvement, participation, attention and difficulty in the classroom all decrease, it means that the students' listening status needs to be adjusted in time. At the same time, teachers should be more vigilant, adjust teaching strategies in a timely manner, activate classroom atmosphere, improve teaching efficiency, and improve teaching effects.

(3) According to the data of individual students' classroom emotional involvement, combined with the progress of classroom teaching, highly targeted learning strategies can be provided for students with learning difficulties. Aiming at the basic learning ability of some students in our school, their study habits lead to the loss of most of their emotional input in classroom teaching is unconscious. Therefore, through the analysis of personal emotional data after class, it is possible to put forward personalized learning strategies and suggestions, change learning habits, optimize learning effect, and improve learning level.

In short, the quantitative analysis of facial expression recognition in classroom teaching can carry out real-time strategic intervention on the teaching and learning input in the classroom teaching process, and can implement teaching strategy optimization through auxiliary decision-making methods at any time, and at the same time, learn learning strategies for learners. Customize, improve the phenomenon of learning difficulties, etc. It has obvious positive guiding significance for teachers and students. However, due to the extreme scarcity of current data, the analysis results do not have general statistical properties.

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