Knowledge-Based Systems 22 (2009) 256–260

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Assessment of affective state in distance learning based on image detection by using fuzzy fusion

Kuo-An Hwang [a], Chia-Hao Yang [b,*]

[a] Department of Computer Science and Information Engineering and Graduate Institute of Networking and Communication Engineering, Chaoyang University of Technology, No. 168, Jifong E. Rd., Wufong Township, Taichung County 41349, Taiwan, ROC
[b] Graduate Institute of Informatics, Doctoral Program, Chaoyang University of Technology, No. 168, Jifong E. Rd., Wufong Township, Taichung County 41349, Taiwan, ROC

ARTICLE INFO

Article history:
Available online 9 January 2009

Keywords:
Fuzzy integral
Distance learning
Image detection

ABSTRACT

Distance learning can solve the limitations of time and space in learning. However, due to the distance, teachers cannot manage students learning behaviors, i.e. they do not know whether a student is attentive, drowsy or absent. Teachers can overcome difficulties in students' management by knowing the affective states of the students. This study adopts image recognition to capture face images of students when they are learning, and analyzes their face features to evaluate their affective states by fuzzy integrals. Test results indicate that the bad affective states are accurately identified. Teachers can monitor the students' affective states from the detection results on the system interface.

1. Introduction

Distance learning has developed rapidly in the recent years. Many schools have built distance learning systems, and currently offer distance learning courses. Students can login to the website freely in their own time to learn online. Students earn credit by completing the coursework set by the school, and by handing over the related reports or completing the evaluations. These courses have two main display methods, namely html and video. They include tests to assess each student's achievement. Students earn credit if they achieve the requirements of a course. Although students can learn at times convenient for them, they might not learn at times when their mood is best and their attention is strongest. This study concludes that effective time management is the best learning strategy, and is a significant factor for academic achievement [1]. Many studies have focused on students' behavior and distance learning efficiency [2]. A teacher assesses each student's achievement from the results of on-line tests [3]. However, while learning assessments focus on the Cognitive Domain of courses to evaluate the teaching result, and they do not address the Affective Domain of learning processing [4].

Hence, some studies have assessed the affective states of learners from their login frequency, and total time that they are involved in learning or discussion [5,6]. However, discussion time does not equal discussion quality. A student who spends more time in discussion does not always participate fully in course discussion [7]. Therefore, many students who join distance learning courses, and who want to earn the credits, just login the system without sitting in front of the computer and studying effectively. However, they still earn course credit. Credits obtained in this way do not help the students to develop good learning attitude during the courses, and do not increase confidence in learning.

Teachers can efficiently manage the learners' states in distance learning processing by monitoring the learners' affective states, and urging the learners with bad learning behavior, such as drowsing, sleeping and leaving class, to study hard. Image recognition systems can monitor a person's affective state from face images, and are widely applied to monitor the states of drivers [8–10]. Image recognition can also be used to monitor students' affective states by adding other detection goals, such as leaving and inactivity in distance learning. Inactivity detection means that the students cannot avoid being detected by wearing masks or fake faces. Recognition systems can be employed to evaluate those behaviors, helping teachers to handle students' learning states.

This study examines the defects of the existing distance learning from the perspective of learning attention. A system is designed and implemented to determine a student's learning condition, in order to help teacher ensure that each student is learning effectively and is paying attention when accumulating the participation hours. This mechanism does not need any additional devices to be installed on computer, except a webcam to capture facial images in real time. The student's attentiveness when participating in courses is then detected by auto-detection from image recognition. Finally, Fuzzy Integral assessment is performed to reduce the probability of misjudgment.

Section 2 explores the Affective Domain teaching goal, and the application of image recognition to identify the expression features

* Corresponding author. Tel.: +886 4 2332 3000x7708; fax: +886 4 2330 4902.
E-mail address: s9433901@cyut.edu.tw (C.-H. Yang).

0950-7051/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.knosys.2008.10.004

in detecting the possible learning condition of the learner. Section 3 describes the design and implementation of the mechanism procedure. Section 4 discusses the membership function of Fuzzy Logic. Section 5 presents the practical evaluation of the accuracy of the detection of image recognition and of the Fuzzy fusion assessment. Finally, the conclusion and the directions for future researches are presented.

2. Related work

Affective Domain teaching goals can be divided into five stages [11]: Receiving or Attending, Responding, Valuing, Organizing and Characterizing [12]. In conventional face-to-face class teaching, teachers generally measure students' affective states from their concentration, responses and participation in class [4]. Okamoto proposed that the most immediate and simple interaction comes from questions and answers. Interactive teaching activities, such as oral evaluation or discussions, improve students' learning interest [13–15].

Image recognition technologies can be utilized to classify the affective states of users from their face images. Gu and Ji identified tiredness with behaviors such as closing eyes, not looking steadily at the front, yawning, turning the head and wrinkling between the eyebrows. Image recognition can be used to detect these mentality situations [16]. Mentality detection methods have been applied to help drivers in maintaining good mental states when driving. If the system shows that a driver has a bad mental state, then it issues a warning to remind the driver to be careful and address driving safety [8,9,17].

Currently, image recognition generally focuses on detecting bad mentality. However, inattention and distraction are also common problems in distance learning situation. A person with these behaviors is in a good mental state, but is not participating in the course. Additional detection mechanisms need to be added to the image recognition to apply it to distance learning [18].

3. Image detection procedure

The main difference between distance learning and class learning is that the teachers and students who participate in distance learning courses are not in the same location. Owing to the distance, teachers cannot observe the students learning situations in a distance learning situation as they can in class learning. The advantage of distance learning is that the students can study via computers and across telecommunication networks.

However, monitoring each student's image, taken by cameras and delivered to the teachers' monitor, easily distracts teachers in a distance learning situation. Detection Technologies in Image Processing can be applied to supervise and monitor students' learning situations automatically, thus decreasing the working loads of teachers, and improving attention of students in class.

Fig. 1 shows the procedure for observing students' behavior. Teachers expect students to learn attentively. Therefore, the system is designed to detect all inattentive behaviors, such as leaving, head turning, drowsiness and lack of motion.

Inattentive behaviors are judged from the features of images. The skin region detection mechanism first transforms the RGB color space into NRGB. The skin color distribution models proposed by Soriano are adopted to define the top and bottom boundaries, and then to eliminate the white color of image, as shown in Eqs. (1)–(3). These three equations are combined to define the skin color region (see Eq. (4)) [19]. Dilation and Erosion are then performed to combine the dividing regions and erase noise. If the region is too small, then the detected skin region from the image is too small, indicating that the student may have left his seat

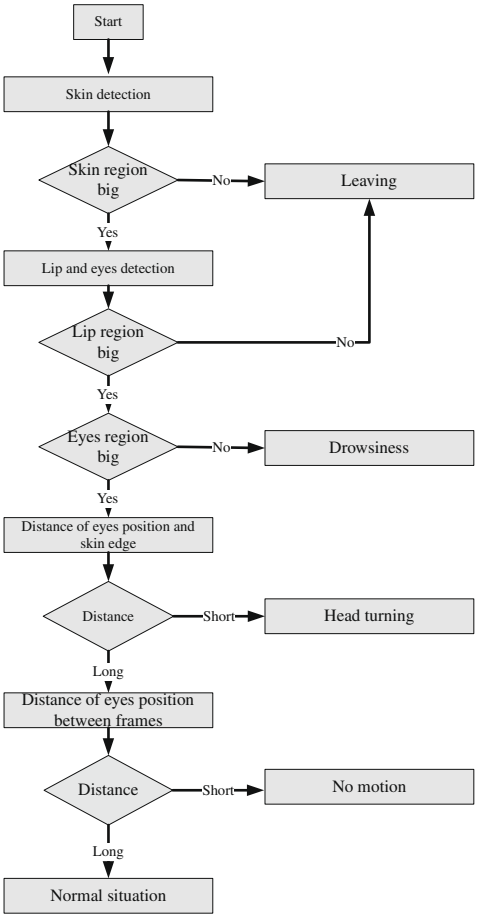

Fig. 1. Affective state detection procedure.

$$Q_+ = -1.3769r^2 + 1.0743r + 0.1452, \quad r = \frac{R}{R+G+B} \tag{1}$$

$$Q_- = -0.776r^2 + 0.5601r + 0.1766, \quad r = \frac{R}{R+G+B} \tag{2}$$

$$W = (r-0.33)^2 + (g-0.33)^2, \quad r = \frac{R}{R+G+B}, \quad g = \frac{G}{R+G+B} \tag{3}$$

$$S(x,y) = \begin{cases} 1 & \text{if } (g < Q_+) \text{and} (g > Q_-) \text{and } (W > 0.004) \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Lips are detected by applying detecting red within skin regions, as in Eq. (1). The red color is identified from the condition, $R - G \geqslant 15$, in Eq. (5). If a skin region contains no red color, then it is not a face region

$$L(x,y) = \begin{cases} 1 & \text{if } (g < Q_+) \text{ and } (W > 0.001) \text{ and } (R - G \geq 15) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The eyes are detected by applying the eyes template. The regions in the eyes template are first defined for comparison with detection image. The template is then applied to identify the facial region and locate the eyes. Then, eyes template and detection image are transformed to gray color space. The gray is then transformed to calculate the mean values of the eye template regions. The facial regions are scanned to compare the normalized