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Facial Gesture Analysis During Online Tutorials

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Abstract—**The facial expression recognition is to detect human emotion based on expression.Facial expression recognition follows the research framework of pattern recognition. This is composed of three steps: detection of face, feature (facial) extraction and expression classification. The amount of research carried out in each of these categories is quite sizable and noteworthy. These three categories areconcerned with the central background pertaining to the issue of facial emotion recognition. Apart from them, another core area is development of appropriate facial database for such studies. The results highlight that specific facial movements predict tutoring outcomes of engagement, frustration, and learning. Particular patterns emerged for almost all of the facial action units analyzed. We discuss each of the results in turn along with the insight they provide into mechanisms of engagement, frustration, and learning as predicted by facial expression.**

Index Terms—**Action ,Facial recognition , Expression, Engagement , Learning , Mechanism**

I. INTRODUCTION

Student engagement is a key concept in contemporary education, where it is valued as a goal in its own right. In this paper we explore approaches for automatic recognition of engagement from students' facial expressions. We studied whether human observers can reliably judge engagement from the face; analyzed the signals observers use to make these judgments; and automated the process using machine learning. We found that human observers reliably agree when discriminating low versus high degrees of engagement (Cohen's _ = 0:96). When fine discrimination is required (4 distinct levels) the reliability decreases, but is still quite high (_ = 0:56). Furthermore, we found that engagement labels of 10-second video clips can be reliably predicted from the average labels of their constituent frames (Pearson r = 0:85), suggesting that static expressions contain the bulk of the information used by observers. We used machine learning to develop automatic engagement detectors and found that for binary classification (e.g., high engagement versus low engagement), automated engagement detectors perform with comparable accuracy to humans. Finally, we show that both human and automatic engagement judgments correlate with task performance. In our experiment, student post-test performance was predicted with comparable accuracy from engagement labels (r = 0:47) as from pre-test scores (r = 0:44).

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II. RELATED WORK

The purpose of this experiment was to measure the importance to teaching of seeing the student's face. In the experiment, video and synchronized task performance data were collected from subjects interacting with cognitive skills training software. Cognitive skills training has generated substantial interest in recent years; the goal is to boost students' academic performance by first improving basic skills such as memory, processing speed, and logic and reasoning. A few prominent systems include Brainskills (by Learning RX [1]) and FastForWord (by Scientific Learning [2]). The Cognitive Skills Training experiment utilized custom built cognitive skills training software (reminiscent of BrainSkills) that we developed at our laboratory and installed on an Apple iPad. A webcam was used to videorecord the students; it was placed immediately behind the iPad and aimed directly at the student's face. The game software in the experiment consisted of three games – Set, Remember, and Sum – that trained logical, reasoning, perceptual, and memory skills. The games were designed to be mentally taxing. Hard time limits were imposed on each round of the games, and the human trainers who controlled the game software (in either the Wizard-of-Oz or 1-on-1 conditions, as described below) were instructed to "push" students to perform the task more quickly. In this sense, the cognitive skills training domain of our experiment might resemble a setting in which a student is taking a stressful exam. In terms of physical environment, typical ITS and the cognitive skills setting in our study are very similar – a student sits directly in front of a computer or iPad, and a web camera retrieves frontal video of the student. It is possible that the appearance of affective states such as engagement might differ between cognitive skills training and ITS interactions. Nevertheless, it is likely that the methodology of labeling and the computer vision techniques for training automated classifiers could still generalize to more traditional ITS use cases. The dependent variables during the 2010-2011 experiment were pre- and post-test performance on the Set game. The "Set" game in our study was very similar to the classic card game: the student is shown a board of 9 cards, each of which can vary along three dimensions: size, shape, and color. The objective is to form as many valid sets of 3 cards in the time allotted as possible. A set is valid if and only if the three cards in the set are either all the same or all different for each dimension. After forming a valid set, the three cards in that set are removed from the board, and three new cards are dealt. This process then continues until the time elapses.

III. Proposed Methodology

Yawning Analysis :

Detection of drives' drowsiness based on yawning measurement. This involves several steps including the real time detection and tracking of driver's face, detection and tracking of the mouth contour and the detection . shows of yawning based on measuring both the rate and the amount of changes in the mouth contour area. automotive smart camera platform developed by Connive In our approach, the driver's face is continuously captured using a video camera that is installed under the front mirror inside the car detecting drowsiness involves two main steps to properly measure changes in facial gestures that imply drowsiness. First, the driver's face is detected and tracked in the series of frame shots taken by the camera. After locating the driver's face, the next step is to detect and track the location of the mouth. We have chosen to detect and track the face prior to tracking the mouth as this makes the mouth tracking procedure more robust against false detections. After detection of the mouth, the yawning state is detected based on measuring the rate of changes in the area of the mouth contour and the aspect ratio of mouth .

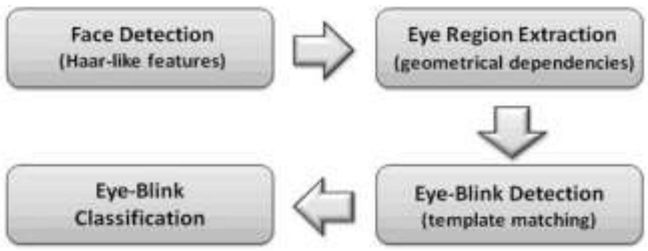

Figure 1

Figure Face And Mouth Detection

Head Nodding :

Another method currently use is the Head Position Detection. This technology simply determines the head tilt angle. When the head angle goes beyond a certain angle, an audio alarm is transmitted in the driver's ear.

IV. Analysis of Problem

A. *Human face Recognition*

Facial Action Coding is a muscle- based approach. It involves identifying the various facial muscles that individually or in groups cause changes in facial behaviours. These changes in the face and the underlying (one or more) muscles that caused these changes are called Action Units (AU). The FACS is made up of several such action units. For example:

- AU 1 is the action of raising the Inner Brow. It is caused by the *Frontalis* and *Pars Medialis* muscles,
- AU 2 is the action of raising the Outer Brow. It is caused by the *Frontalis* and *Pars Lateralis* muscles,
- AU 26 is the action of dropping the Jaw. It is caused by the *Masetter*, *Temporal* and *Internal Pterygoid* muscles, and so on [10]. However not all of the AUs are caused by facial muscles.

Some of such examples are:

- AU 19 is the action of 'Tongue Out',
- AU 33 is the action of 'Cheek Blow',
- AU 66 is the action of 'Cross- Eye', and so on [9,10].. The Face can be divided into Upper face[11] and Lower Face Action units[12] and the subsequent expressions are also

identified. The Figures shows some of the combined action units.**side of your figures.** Use the abbreviation "Fig." even at the beginning of a sentence. Do not abbreviate "Table." Ta RESEARCH(IJSETR)" in the title of this article).

V. Conclusion

This paper presented an automated facial recognition approach to analyzing student facial movements during tutoring using the Computer Expression Recognition Toolbox (CERT), which tracks a wide array of well-defined facial movements from the Facial Action Coding System (FACS). CERT output was validated by comparing its output values with manual FACS annotations, achieving excellent agreement despite the challenges imposed by naturalistic tutoring video. Predictive models were then built to examine the relationship between intensity and frequency of facial movements and tutoring session outcomes. The predictive models highlighted relationships between facial expression and aspects of engagement, frustration, and learning. This novel approach of fine-grained, corpus-wide analysis of facial expressions has great potential for educational data mining. The validation analysis confirmed that CERT excels at tracking specific facial movements throughout tutoring sessions. Future studies should examine the phenomena of facial expression and learning in more detail. Temporal characteristics of facial expression can also be examined, such as how rapidly an expression appears and how quickly it vanishes. Additionally, with these results in hand, it will be important to conduct an analysis of the broader set of facial action units tracked by CERT to build a comprehensive understanding of the interplay between learning and affect.

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